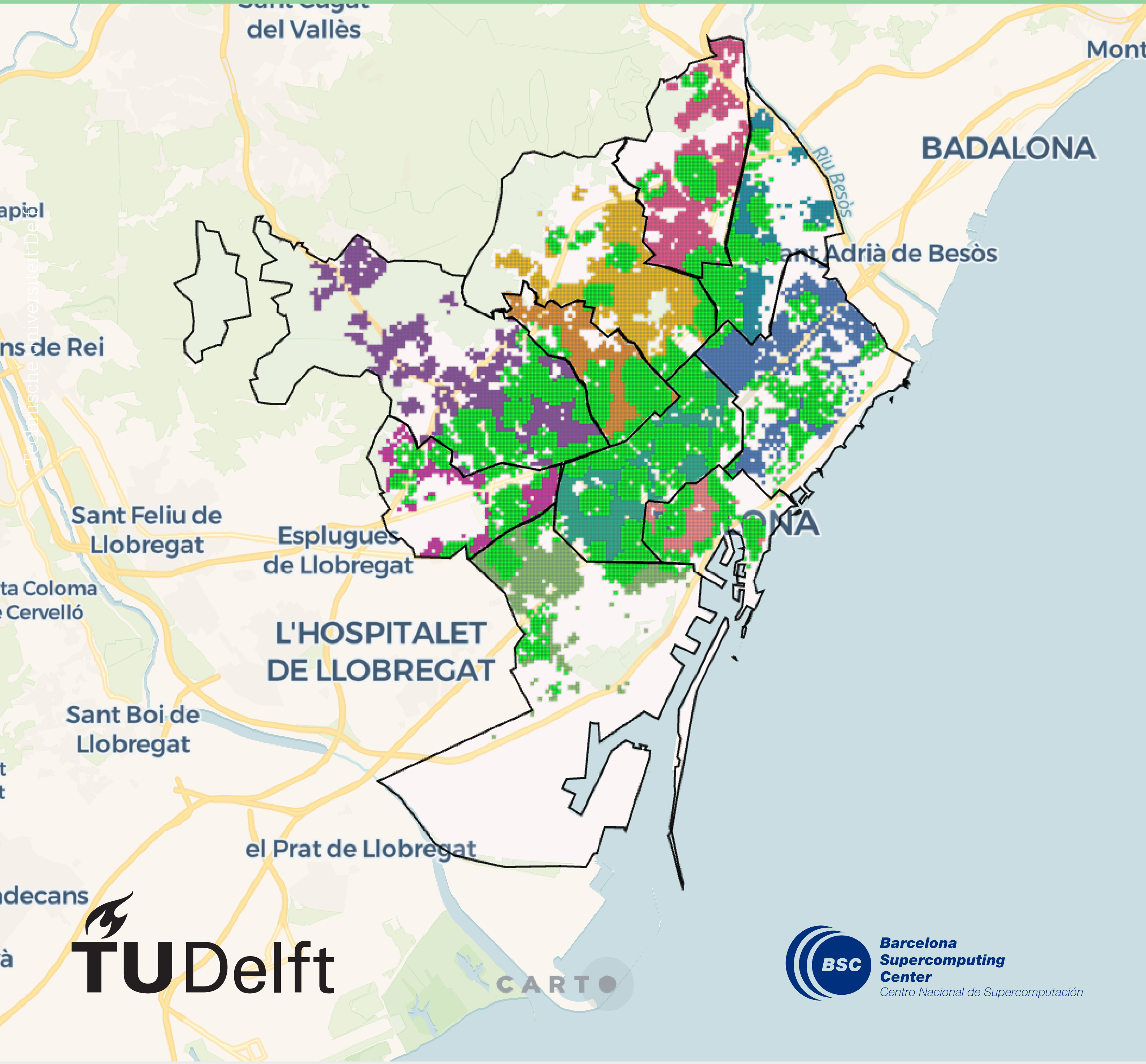
Circular City Index

MDP Project Barcelona

CEGM3000: MDP Project

Maaike Kuipers, Cato Martens, Daan Bozon, Tijn van Beeck and Juul Hemmes



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Centro Nacional de Supercomputación

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by

Maaike Kuipers, Cato Martens, Daan Bozon, Tijn van Beeck and Juul Hemmes

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Preface

This report is written for the Barcelona Supercomputing Centre (BSC) as part of the Urban Data Science department. It reflects our collaborative efforts with Patricio Reyes, Serena Mombelli, Roger Gonzales March, Fernando Cucchietti, Sol Bucalo Mana and Luca Liebscht, whose guidance and support were invaluable throughout the project. We would also like to extend our gratitude to Maarten Kroezen and José Álvarez Antolínez from TU Delft for their supervisory role and insightful feedback.
Working on this project was both enjoyable and enriching, providing us with valuable learning experiences and a great professional environment at BSC. We hope this research contributes meaningfully to the Municipality of Barcelona in its efforts to efficiently promote circularity within the city's districts.

Maaike Kuipers, Cato Martens, Daan Bozon, Tijn van Beeck and Juul Hemmes
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Summary

The Circular City Index (CCI) project for Barcelona, conducted in partnership with the Barcelona Supercomputing Center, aimed to assess urban circularity across multiple districts. Utilizing the City Circularity Index model as introduced by Muscillo et al. (2021), this research adapted the framework to Barcelona's unique urban context, focusing on the four main components: Digitalization (D), Energy, Climate and Resources (ECR), Mobility (M), and Waste (W). The project benchmarks city performance against Sustainable Development Goals (SDGs) to guide strategic planning for a sustainable and resilient urban environment.

Each district's performance was measured through tailored Key Performance Indicators (KPIs) reflecting accessibility, infrastructure, and environmental data. Spatial and statistical analyses were applied to assess parameters such as waste collection accessibility, air quality, and renewable energy coverage. Data was gathered from open-source and municipal datasets, complemented by geographic analysis for a precise district-level understanding.

The analysis revealed considerable variability among districts, particularly in energy production, waste management, and air quality:

- **Digitalization:** Wi-Fi accessibility was high overall, but districts like Sarrià-Sant Gervasi showed lower coverage, indicating digital infrastructure disparities.
- **Energy, Climate, and Resources:** Solar energy production varied across districts, with several areas falling short of self-sufficiency targets, highlighting the need for expanded solar initiatives. City-wide improvements are needed in air quality and EPC label. Water usage also showed a lot of variation, influenced by factors such as population density and tourism.
- **Mobility:** Public transport access is excellent throughout Barcelona, with all districts meeting accessibility thresholds for transit stops. Pedestrian area availability is higher in suburban districts, though densely populated zones like Eixample show limited pedestrian space per capita. Cycleway and bike-sharing station distribution is uneven, with central districts like Sant Martí scoring high, while suburban areas see lower availability.
- **Waste Management:** Waste production was highest in districts like Ciutat Vella, influenced by high tourist activity, while recycling access was limited in areas like Nou Barris. E-waste collection points are sparse in Sarrià-Sant Gervasi, and expanding these could enhance waste management effectiveness across districts.

To enhance circularity, the project recommends targeted interventions:

- Citywide Solar Expansion: Address energy disparities by promoting solar installations, particularly in underserved districts.
- Comprehensive Air Quality Plans: Implement broader policies to address emission reductions across all districts.
- Waste Management Enhancements: Expand waste collection accessibility and recycling facilities, particularly in districts with low recycling rates.
- Mobility Infrastructure: Increase pedestrian areas and improve bike-sharing access, especially in mobility-limited areas.

The findings provide actionable insights for the Municipality of Barcelona to foster a sustainable and circular urban ecosystem, aligning with broader SDG objectives as set for 2023.

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1
Introduction

Cities are the largest consumers of global resources and the biggest producers of waste. Despite covering only 3% of the Earth's surface, they house over 55% of the population, a figure projected to rise to 70% by 2050. Cities consume 75% of global resources, generate between 50% and 80% of greenhouse gas emissions, and produce half of the world's waste. This unsustainable consumption poses one of the most pressing challenges for modern society (Lucertini & Musco, 2020). The importance of addressing urban sustainability is reflected in global initiatives such as the Sustainable Development Goals (SDGs), particularly SDG 11, which aims to create inclusive, safe, resilient, and sustainable cities and communities. Yet, despite these initiatives, cities often lack comprehensive and adaptable strategies to tackle sustainability issues effectively. The complexity of geographical, political, and socio-economic factors further complicates the task of developing appropriate sustainability metrics, especially at the municipal level (Nations, 2015).

The need for improved environmental policies and better management of sustainability challenges reflects broader issues faced across Europe. The circular economy framework has emerged as a promising approach to address these issues by introducing innovative solutions and measuring environmental impact.
While the European Union and the United Nations have incorporated circular economy strategies, such as the SDGs and the Circular Economy Action Plan, there is still no standardized approach for evaluating and tackling sustainable development challenges at the municipal level. This gap represents a critical issue in both policy and academic literature.
To address this gap, the Circular City Index (CCI) was initially developed in Italy as a tool for assessing the circularity and green transitions of municipalities. The CCI evaluates cities based on four key areas: digitalization, environment and energy, mobility, and waste management, using open data to inform policy decisions (Muscillo et al., 2021).
Barcelona, with its diverse districts, serves as an ideal case for applying CCI principles. The city faces significant environmental and social disparities across its districts, making it crucial to develop localized sustainability factors focused on areas such as infrastructure, mobility, and waste management. Through the use of open data, policymakers could craft customized strategies that promote digital, energy, and ecological transitions while remaining inclusive of the distinct demographic and socio-economic profiles of each district (Muscillo et al., 2021).
This research aims to adapt and refine the CCI for application in Barcelona's districts, examining their readiness for urban circularity and green transitions. This adaptation seeks to provide insights that can guide policymakers in creating localized sustainability strategies. Ultimately, by tailoring the CCI to the context of Barcelona, this study aims to enhance urban planning efforts and contribute to the city's transition toward a more sustainable and resilient future.

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Background and Literature Review

The global shift towards sustainable development, initiated in 1992, marked the beginning of a new era. It became clear that human needs and aspirations needed to be balanced with maintaining healthy ecological and social systems. Development could no longer be justified purely on economic grounds without considering its wider environmental, social, and sustainability impacts. This shift in the understanding of development created a demand for information and guidelines to achieve sustainability across all dimensions.

In response, new progress indicators were introduced to complement traditional measures of development, which primarily focused on economic factors. Building on early work by Stiglitz (2011), the OECD (2011), and the European Commission (2009), a significant wave of indicator production followed, covering various policy areas, including sustainable development in local communities and cities. These indicators often aggregate diverse information and serve as tools for ranking and comparing public policy outcomes. Building upon the early work, Rens Van Wijk (2023), produced the the Indicator Criteria Framework for Testing Circular Economy Indices. This framework divides the 7 most important topics with their accompanying subtopics, as shown in Table 2.1.

Table 2.1: Overview of the Circular Economy Topics

Categorized Topic	**Sub-topics examples**
Waste	e-waste; food waste; industrial waste; municipal waste; (solid) waste generation; waste recycle;
Energy	energy consumption; energy dependence; energy productivity; industrial energy consumption; renewable energy
Water	water consumption; water irrigation; water leakage; wastewater recycling; water withdrawal
Environment	CO2 emissions; green policy; natural resource renewables; NOx emissions; NO_2 emissions; emission reduction targets; SO2 emissions
Mobility	15-minute city; cycleways; e-charging stations; footways; pedestrian areas; public transport
Information and Technology	data accessibility; environmental technology; green institutions; green organizations; internet broadband connection; public digital identity system; technology patents;
Economy	circular jobs; green employment; green finance; green economic growth; green economic investments; supply chain

To track the progress of sustainability in Europe, various city rankings have been developed to assess the environmental sustainability of European cities. These rankings play a role in evaluating and shaping environmental policies in European cities.

However, they come with several limitations and methodological challenges. Due to differences in methodologies, a city can rank highly in one assessment while scoring poorly in another. The identified indices are shown in Table 2.2.

Analyzing the benefits and drawbacks of the indices is important to evaluate their ability to perform a complete evaluation. Except for the CCI, each index lacks a focus on one or more essential elements to enable the measurement of circular economies at different macro-levels. The only indices that almost incorporate all topics in six out of seven subjects are the Green Growth Index and the Circular Cities

Table 2.2: Overview of the Circular Economy Indices

Indicator	**Number of categories**	**Number of Indicators**
Circular City Index	4	17
European Green Capital Award 1	NA	12
European Green City Index 2	8	30
Urban Ecosystem Europe	6	25
Circular Economy Monitoring Framework	4	10-19
Green Growth Index	4	16-36
National Circular Economy Indicator System	4	22
Circular Economy approach for China	4	9
Evaluation System of Regional Circular Economy Development Level	4	16
Comprehensive Index of Circular Economy	3	10
Circular Cities Barometer	4	12
Circular Cities in Indonesia	6	23
Zero Waste Index	2	6

Barometer. However, the Green Growth Index measures its indicators at a national level. At city level, the only comparable index to the CCI is the Circular Cities Barometer. Though, this barometer has not yet been applied at the municipal level, which gives the CCI an advantage for multi-level implementation. In addition to this, the preference in this research is the CCI, because the knowledge about this Indice is great within the company Barcelona Supercomputing Centre. The overview of the categorized topics of the Circular Economy incorporated by the indices is shown in Table 2.3.

Table 2.3: Categorized Topics of the Circular Economy Incorporated by the Indices

Research	**Incorporated Circular Economy Topic**						
	Waste	Energy	Water	Environment	Mobility	Information & Technology	Economy
Circular City Index	X	X	X	X	X	X	
European Green Capital Award 1	X	X	X	X			
European Green City Index 2	X	X	X	X	X		
Urban Ecosystem Europe	X	X	X	X			
Circular Economy Monitoring Framework	X					X	X
Green Growth Index	X	X	X	X		X	X
National Circular Economy Indicator System	X	X	X	X			
Circular Economy approach for China	X	X	X	X			
Evaluation System of Regional Circular Economy Development Level	X	X	X	X			X
Comprehensive Index of Circular Economy	X	X	X				
Circular Cities Barometer	X	X	X	X	X		X
Circular Cities in Indonesia	X	X	X	X			X
Zero Waste Index	X	X	X	X			

3
Methodology

In this chapter, the research methodology is outlined in detail. First, the methodology used by Muscillo et al., 2021 for the implementation of the Circular City Index (CCI) in Italy is critically examined. Per segment, the necessary adaptations for applying the CCI to the context of Barcelona are discussed. Finally, the chapter presents the refined set of key performance indicators (KPIs) tailored to the district-specific index for Barcelona. The indicators will be linked to the circularity goals of the city of Barcelona based on the corresponding SDG's, as stated by the European Union (Ajuntement Barcelona, 2020). Additionally, a threshold or benchmark value is established to assess the performance of each district across the different indicators. Lastly, the calculation of the CCI is discussed.

3.1. KPI Analysis

The study by Muscillo et al., 2021 is based on the City Circularity Index (CCI), which includes four segments: Digitalization (D), Energy, Climate and Resources (ECR), Mobility (M), and Waste (W). While these segments remain relevant, not all their indicators apply to Barcelona. This is because some indicators are specific to Italian cities, as noted by Muscillo et al., 2021. The first adaptation of this set of KPIs was made by Van Wijk, 2023 to implement the CCI across all municipalities in Spain at the national level. This research further examines these indicators to determine which can be excluded, while adding others relevant at the district level.
First, the indicators excluded from previous reports will be identified, followed by a more detailed explanation of the indicators included in and added to this research. The KPIs defined by Muscillo et al., 2021 are presented in Table 3.1.

3.1.1. Digitalization (D)

Regarding the Digitalization segment, none of the KPIs used by Muscillo et al., 2021 are considered in this research. In Spain, the equivalents of the ANPR and SPID systems are PAe and Cl@ve, respectively. The decision to exclude these KPIs is based on the fact that *Presence in PAe* and *Adoption of Cl@ve in PA Digital Properties* are nationwide policies that cannot be differentiated at the district level within Barcelona. Furthermore, Barcelona is already present in the PAe system ("PAe - Portal de la Administración Electrónica", 2015), and Cl@ve is already implemented across public administration in the city (C. C. Barcelona, 2024; OBSAE, 2024).
The same reasoning applies to D4: *Accessibility of Local Government Digital Properties.*
Additionally, KPI D3: *% of People with Broadband Internet Connection (>30 Mb/s)* is not relevant, as 99.95% of Barcelona is already covered by fixed wireless access, and 4G coverage reaches 100% ("S.E. de Digitalización e Inteligencia Artificial y S.E. de Telecomunicaciones e Infraestructuras Digitales - Información de cobertura", 2023). This makes it a less urgent target for the city to address.
For this research, a fifth indicator has been added to the Digitalization segment: Wifi Accessibility (D1), which is considered the only relevant indicator for this category.

D1: WiFi Points

This KPI was introduced to evaluate the level of digitalization across different districts by measuring the percentage of households within a 10-minute walking distance from a WiFi access point. WiFi accessibility provides insights into the advancement of digital infrastructure in each district. Moreover, the availability of public WiFi points can serve as a key indicator of social inclusivity, offering internet access to individuals without personal broadband connections. Lastly, it brings convenience, allowing

Table 3.1: Definition of KPIs for the case study of Muscillo et al., 2021

Level	Sub-level	KPI	Definition
Digitalization (D)	Public digital identity system	D1	Presence in ANPR (public digital service platform)
		D2	Adoption of SPID in PA digital properties
	Broadband internet connection	D3	Percentage of people with broadband connection (> 30Mb/s)
	Data accessibility	D4	Accessibility of local government digital properties
Energy, Climate and Resources (ECR)	Emission reduction targets	ECR1	Covenant of Mayors - Subscription
		ECR2	Covenant of Mayors - Level of commitment
	Energy consumption	ECR3	Percentage self-consumption (household only)
	Air quality	ECR4	Annual average concentration of PM_{10}
		ECR5	Annual average concentration of NOx
	Water efficiency	ECR6	Percentage of water leaks
Mobility (M)	Pedestrian Area	M1	Pedestrian areas (m^2/100 inhab.)
	Charging stations for electric vehicles	M2	Charging stations (charging station/1,000 inhab.)
	Cycle lanes	M3	Cycleways (km/100 km^2)
	Public transportation availability	M4	Transit Stops (stops/100 inhab.)
Waste (W)	Production of solid waste	W1	Per capita production of solid waste (t/inhab.)
	Recycling of waste	W2	Percentage of solid waste recycling
	Collection of e-waste	W3	Collection of e-waste

people to stay connected regardless of their financial situation or location (Smartcity, 2023). This is aligned with Sustainable Development Goal 9C & 9.4. The calculation of variables at the 10-minute distance is explained in detail in Section 3.3.

3.1.2. Energy, Climate and Resources (ECR)

While most of the ECR indicators from the original CCI have been retained, the indicators *Covenant of Mayors - Subscription* and *Level of Commitment* have been omitted from this project. The reason for this is that the Covenant of Mayors is a national initiative, and since all districts in Barcelona fall under the same city administration, they share the same mayor. Other indicators have been added or adapted. Firstly, *% of Energy Self-Sufficiency (from Renewables)* has been adapted to *% of Energy Self-Sufficiency (from Renewables by Municipal Buildings)* per district (ECR1). This is complemented by a newly introduced indicator: *EPC Labels* (ECR4). Together, these indicators are used to analyze energy consumption. Secondly, the indicators *Annual Average Concentration of PM_{10}* and *Annual Average Concentration of NOx* have been combined into a single indicator: *Air Quality* (ECR2). Lastly, the original indicator *% Water Leaks* has been revised to *Water Efficiency* (ECR3). The new indicators are elaborated upon in the next section.

ECR1: Energy Self-sufficiency

This indicator has been added to represent the goal of increasing locally generated sustainable energy. Despite the high number of sun hours, Spain has a relatively low number of solar panels due to limited consumer-level information (Gorgi, 2024) and the so-called "solar tax" (Cunatweber, 2015). Under this tax, electricity producers face additional taxes on self-generated energy, while any surplus electricity fed back into the grid does not result in compensation for the producer. Combined with the fact that municipal buildings and facilities account for around 50% of the total municipal energy expenditure (A. de Barcelona, n.d.-c), this situation highlights the need for municipal intervention, aligned with the goal set in SDG 7.3.

These interventions are outlined in the Municipal Buildings Energy Improvement Plan (PEMEEM), which aims to reduce energy consumption and install renewable energy sources on municipal buildings (A. de Barcelona, 2023b), as well as in the Program to Promote Solar Power Generation in Barcelona, which encourages the use of rooftops and public spaces for energy generation (A. de Barcelona, 2023a). To assess the percentage of energy demand that municipal buildings can supply per district, the total kWh supplied is divided by the total kWh consumed per district.
For this KPI, only solar power generated by solar panels on municipal buildings is considered. Additionally, it is compared solely to electrical energy consumption; other energy sources, whether consumed or generated, are not included in this analysis.
Furthermore, the municipality's SDG target is not directly applicable to this KPI. Therefore, a quartile-up normalization is applied to scale the districts relative to each other, as further discussed in section 3.3.

ECR2: Air Quality

In this indicator, the average annual concentration of $PM_{2.5}$, PM_{10}, and NO_2, measured in $\mu g/m^3$, has been aggregated. While only PM_{10} and NO_2 were analyzed in the research conducted by Muscillo et al., 2021, this study also includes $PM_{2.5}$. As a direct byproduct of car exhaust fumes and a primary component of smog, both $PM_{2.5}$ and PM_{10} are considered harmful to human health (Smith, 2020). However, the municipality of Barcelona has consistently failed to keep the average annual concentration of these pollutants at or below the WHO standards (WHO, 2021). Regarding NO_2, given that EU-wide emissions legislation has been in place for some time, cities must reduce nitrogen dioxide emissions from all possible sources (EEA, 2018). Lowering the concentration of these substances in the air is directly linked to improving air quality. This indicator may provide valuable insights for the municipality of Barcelona, helping to identify potential improvements in air quality and emission reduction at the district level, thus connecting it to SDG 11.6.

ECR3: Water Efficiency

In the original CCI, this indicator was labeled as *% Water Leaks*, which was omitted in the first Spanish adaptation by Van Wijk (2023) due to a lack of data. The same data limitation applies to Barcelona, yet water scarcity remains a critical issue, closely related to SDG 6.4 and the city's own goals to improve urban water efficiency in response to increasing droughts in Catalonia (A. de Barcelona, 2022). Therefore, the indicator has been modified from *Water Leaks* to *Water Efficiency*, measured in liters per inhabitant per day, to analyze which districts in Barcelona could improve their water usage.

ECR4: EPC Labels

ECR4 is a new indicator that tracks the Energy Performance Certificate (EPC) of buildings in Barcelona, rated on a scale from A to G. It reflects the energy efficiency of a property, consisting of both an energy label and an energy plan ((IEA), 2024). By analyzing the performance of buildings at the district level, this indicator helps assess the energy efficiency of the built environment. Using this information, policies can be developed to promote home improvements, reducing energy waste in specific areas. This is linked to SDG 7.1, which focuses on ensuring adequate indoor temperature in homes at all times.

3.1.3. Mobility (M)

Indicators M1, M2, M3, and M4 have been directly adopted from Muscillo et al., 2021, with a few modifications to the units for M3 and M4. Additionally, M2, M3, and M5 have been adjusted to reflect the percentage of households within a 5-minute walking distance, providing a more accurate measure of accessibility. How this percentage is calculated is described in detail in section 3.3. In addition, a new indicator has been introduced, being a key aspect of Barcelona's mobility transition strategy: *E-Sharing Bikes* (M5). All of the indicators in this section are related to Sustainable Development Goal (SDG) 11.2 and align with the municipality's objectives for sustainable mobility.

M1: Pedestrian Area

As the municipality states, the everyday activity of travelling on foot is very beneficial to our health and is also the most economical, efficient and equitable way of travelling, with zero pollution (A. de Barcelona, 2018b). Being the most sustainable way of transport, the indicator is thus adopted in this study and measured in m2 of pedestrian area per 100 inhabitants.

M2: Charging Stations

Barcelona is actively promoting the use of electric vehicles as part of its broader strategy to reduce emissions and combat climate change (A. de Barcelona, 2018a). The city is constantly expanding its network of public and private charging stations to facilitate EV use and aims to make electric mobility accessible to both personal and commercial users. In addition to measuring the number of charging stations per 1,000 inhabitants, the indicator has been adjusted to reflect the percentage of households within a 5-minute walking distance of a charging station. This modification aligns with SDG 11.2 and can also be related to SDG 9, emphasizing accessibility and infrastructure development for sustainable mobility.

M3: Cycleway Lengths

Barcelona is committed to implementing a safe, sustainable, fair and efficient transport model, prioritizing non-polluting forms of transport. This includes promoting more bicycle use as a common urban transport option. In line with this goal, the city government introduced the municipal cycling strategy, which demonstrates a strong commitment to encouraging cycling as a sustainable alternative. This initiative offers significant environmental benefits, reduces reliance on private motor vehicles and frees up road space for community life (A. de Barcelona, n.d.-a). On this basis, this study chose to maintain the same M3 factor. However, since the square footage of Barcelona itself only amounts to about 100km2, the order of magnitude had to be scaled down from km/100km2 to km/km2 to accommodate this area.

M4: Transit Stops

Specifically for Barcelona, the original indicator M4 was modified to include all public transport options. This reflects the broader approach to mobility in forward-looking strategies as Transports Metropolitans de Barcelona's Strategic Plan 2025 (Transports Metropolitans de Barcelona, 2015). This plan, developed through a participatory process with input from various stakeholders, sets targets for reducing carbon emissions and increasing the use of public transport. By revising M4 to take into account all public transport options (bus stops, metro stations and tram stations), we align our mobility assessment with a Barcelona-specific approach to urban transport that prioritizes sustainability and improved access to public transport networks. To measure public transport coverage, the indicator is expressed as the % of households within a 5-minute walk of a public transport stop, rather than through an assessment, as in the municipal target. This allows focusing on the actual accessibility of transport rather than public satisfaction.

M5: Bike-sharing Points

In response to the growing need for sustainable and flexible mobility options, Barcelona has implemented a bike-sharing system that includes both traditional and electric bicycles. The city's bike-sharing program, Bicing, offers residents and visitors an accessible, affordable, and available alternative to motor vehicles. By expanding the number of shared bikes, including electric ones, the city not only promotes active transport but also reduces its carbon footprint. This aligns with Barcelona's goal to achieve more sustainable urban mobility, as outlined in the 2024 Mobility Strategy (Ajuntament de Barcelona, 2020). Since the number of docking stations in Barcelona doesn't necessarily provide a full picture—due to the lack of data showing bike availability per minute—it is decided to focus on the percentage of households that can reach a docking station within a 5-minute walk. This approach is logical because it better reflects the accessibility of the bike-sharing system to residents. By considering proximity rather than the sheer number of stations, we can assess how practical and convenient the system is for daily use, regardless of real-time bike availability.

3.1.4. Waste (W)

Barcelona's Zero Waste Strategy, launched in 2016, focuses on reducing waste, reusing materials, and improving recycling, especially for organic matter. The xgoal is to reach 60% selective waste collection, aligning with EU and Catalonia targets (Ajuntament Barcelona, n.d.-a). In this report, the KPIs for the Waste segment remain similar to the original research by Muscillo et al., 2021 with small adjustments to W2 and W3, as they adequately capture the city's progress toward these goals without requiring modifications.

W1: Waste Production

The Zero Waste Strategy, launched in 2016, seeks to reduce the overall production of solid waste by promoting waste prevention, reuse, and recycling initiatives. (Ajuntament Barcelona, n.d.-b) This initiative aligns with SDG 12.2, through which the city of Barcelona aims to reduce solid waste production to 1.20 kg per inhabitant per day (**ajuntamentbarcelona_2020_**). Accordingly, this indicator will measure the total mass of solid waste generated in kg per inhabitant per day.

W2: Waste Recycling

The municipality of Barcelona has set an ambitious target to increase its recycling rate to 65% of collected waste by 2030 (Ajuntement Barcelona, 2020). This aligns with both EU and Catalonia's broader waste management goals and forms a key component of Barcelona's Zero Waste Strategy.
Given the importance of recycling in achieving a circular economy, the availability and accessibility of recycling infrastructure play a crucial role. Due to the lack of specific data on actual recycling rates at the household level, this indicator has been adapted to measure the percentage of households with access to a recycling bin within a five-minute walk.

This approach is used to approximate the city's capacity to facilitate recycling and serves as a practical measure of how well-equipped the city is to meet its recycling targets. By increasing the accessibility of recycling facilities, the city can enhance recycling rates and encourage greater participation of residents in the waste separation process.

W3: e-Waste Collection

Barcelona has established an extensive Green Point Network for waste management, including the recycling of electronic waste (Ajuntament Barcelona, n.d.-a). Green Points provide a solution for waste that cannot be disposed of in street containers, such as the containers analyzed in W2. Using this service contributes to improving the recycling process and helps preserve the environment.

This network is divided into Neighborhood Green Points and Area Green Points. Neighborhood Green Points offer convenient drop-off locations for residents, whereas Area Green Points focus largely on waste from commercial and service sectors. Mobile Green Points are also deployed to specific locations at set times, providing further accessibility for citizens. This decentralized system ensures that e-waste recycling services are accessible across the city.

The unit of measurement for evaluating the distribution of these services across districts will be the percentage of households within a 10-minute walking distance of a Green Point. Unlike the binary unit used in the work of Van Wijk (2023) and Muscillo et al. (2021), this metric reflects the proportion of households served.

Table 3.2: Definition of the KPIs, weights and target values used in the case study.

Area	Area Weight	KPI	Description	KPI Weight	Type	Unit	Target	Target Source
Digitalization	0.1	D1	Number of WiFi Points	1	%	% of household within 10 min walking distance of WiFi point	99%	SDG 9C & 9.4
Energy, Climate and Resources	0.3	ECR1	% of Local Energy Self-sufficiency (from Renewables by Municipal Buildings)	0.3	%	Generated / Consumed [kWh/y]	6.5 %	SDG 7.2
		ECR2	Air Quality	0.2	Scalar	$\mu m/m^3$	NO_2<40; PM_{10}<20; $PM_{2.5}$<10	SDG 11.6
		ECR3	Water Efficiency	0.3	Scalar	l/inhab/day	<150 l/inhab/day	SDG 6.4
		ECR4	EPC Labels Residential Buildings	0.2	Level	Label A-G	>20% label-C or higher	SDG 7.1 & 7.3
Mobility	0.3	M1	Total Surface of Pedestrian Areas	0.2	Scalar	m^2/100 inhab	900	SDG 11.2
		M2	Total Charging Stations	0.2	Scalar	% of households within 5 min walking distance of charging point	1	SDG 9 & 11
		M3	Total Length of Cycleways	0.2	Scalar	km/km^2	4	SDG 11 & 13
		M4	Public Transit Stops	0.2	%	% of households within 5 min walking distance of public transport option	95 %	SDG 11.2 & Urban Mobility Plan
		M5	Bicycle Sharing Points	0.2	%	% of households within 10 min walking distance of a shared bicycle point	90 %	SDG 11.2 & Urban Mobility Plan
Waste	0.3	W1	Production of Waste	0.4	Scalar	kg/inhab/day	< 1.2 kg/inhab/day	SDG 12.5
		W2	Solid Waste Recycling	0.4	%	% of household within 5 min walking distance of Recycling Bin	65 %	SDG 12.5
		W3	Collection of e-Waste	0.2	%	% of household within 10 min walking distance of Greenpoint	80 %	

3.2. Calculation of Percentage Households Within a Walking Distance

To calculate the percentage of households within a walking range, firstly the coordinates of each data point of each KPI had to be calculated by using their accompanying longitude and latitude. To calculate the walking distance from these data points, the platform Carto was used. Carto is a cloud-based platform that enables users to visualize and analyze geographic data. It offers tools for creating interactive maps and performing spatial analysis, making it useful for industries like urban planning, logistics, and environmental management. With Carto, users can import data, apply spatial analysis techniques, and gain insights into geographic patterns and trends, helping to make data-driven decisions. It supports various data sources and integrates with other GIS tools for more advanced analysis. Within this platform, the data of the coordinates were adapted using the workflow tool. Isolines were added to the coordinates in which the walking distances of 5 or 10 minutes were applicable. This was then done by using a spatial constructor which calculated these distances. This created an area of the walking distances around each coordinate.

Subsequently to this, the data of the households was analyzed. The database that was used for this, obtained through the Barcelona Supercomputing Center, first shows in which areas of Barcelona are households, with a size of 100x100m. Then, by analyzing the row n_finca in the database, we calculated which areas of the 100x100m are inhabited. A new database was created from this using Python. By combining the databases with the isolines from each coordinate and the database with the inhabited 100x100m areas, the area of the covered households is calculated. By comparing the households covered and the total households, the percentage is calculated. This is all done in the program Python.

3.3. Calculation of the Circular City Index

Muscillo et al., 2021 developed an index formula to measure how prepared municipalities are for urban circularity and the green transition. The formula captures both direct and indirect factors that influence these processes at the municipal level, weighting each factor according to its significance for policymakers. The formula introduced by Muscillo et al., 2021 is as follows:

$$CCI_c = \sum_{A \in Areas} \left(W_A \sum_{k \in KPI(A)} W_k \times S_{kc} \right) \tag{3.1}$$

This combines the different areas of interest with the specific KPI weights. To measure the KPIs correctly and make an insightful comparison the KPIs need to be normalized. The normalized KPI value is represented in the formula as S_{kc}.

Normalization of KPIs

The KPIs used in this report are all of different natures. Therefore, different methods are necessary to correctly normalize the found values. 5 different types of normalization are distinguished in this report:

1. **Percentage normalization:**

$$S_{kc,p} = \min\left(\frac{\text{kpi}}{\text{target}}, 1\right) \tag{3.2}$$

   The method for percentage normalization used in this report differs from the approach outlined by Muscillo et al., 2021. Muscillo et al., 2021 applied the normalization scale strictly in relation to an ideal target of 100%. However, the municipality of Barcelona has established specific SDG goals for the various KPIs, as summarized in Table 3.2. Therefore, Equation 3.2 is applied in this report. The normalized value is capped at 1 when the target is achieved. Equation 3.2 is used for the following KPIs: D1, M2, M4, M5, W2, and W3.

2. **Threshold down:**

$$S_{kc,td} = \frac{1}{n} \sum_{i=1}^{n} \begin{cases} \frac{\text{target}_i}{\text{kpi}}, & \text{if kpi} > \text{target}_i \\ 1, & \text{otherwise} \end{cases} \tag{3.3}$$

   The approach outlined by Muscillo et al., 2021 has been adapted in this report. Instead of using a function that evaluates the KPI values across specific intervals, linear normalization is applied.

This method offers a more continuous scoring of KPI values. The threshold-down function is also capped at one. Equation 3.3 is used for ECR2, which includes three air quality indicators, where $n = 3$. Equation 3.3 is also used for KPIs ECR3 and W1, with $n = 1$.

3. **Threshold up**:

$$S_{kc,tu} = \begin{cases} 0, & \text{if target} = 0 \\ 1, & \text{if kpi} \geq \text{target} \\ \frac{\text{kpi}}{\text{target}}, & \text{otherwise} \end{cases} \tag{3.4}$$

The threshold-up normalization follows the same approach as described by Muscillo et al., 2021. Equation 3.4 is applied for KPIs M1 and M4.

4. **Quartile-up normalization:**

$$\text{Upper Quartile} = Q_{75} = \text{percentile}(\text{all kpis}, 75) \tag{3.5}$$

$$S_{kc,qu} = \begin{cases} \frac{\text{kpi}-\min(\text{all kpis})}{Q_{75}-\min(\text{all kpis})}, & \text{if kpi} \leq Q_{75} \text{ and } Q_{75} \neq \min(\text{all kpis}) \\ 0, & \text{if } Q_{75} = \min(\text{all kpis}) \\ 1, & \text{if kpi} > Q_{75} \end{cases} \tag{3.6}$$

While Muscillo et al. (2021) only used a quartile-down normalization, this was transformed to a quartile-up normalization formula for this research due to a lack of applicability. The formula compares the KPI values of districts to one another. A value existing in the upper quartile leads to a score of 1, while a value equal to or lower than this upper quartile leads to a score equal to the proportion of the value in relation to the upper quartile. Regarding its application to ECR1, it was decided to ignore the target value of SDG 7.2 and work with the upper-quartile function, since this target focuses on total local energy production, while the used dataset focuses only on local energy by municipal buildings. This is a share too little to be compared to this cumulative target.

5. **EPC labels normalization:**

$$\text{label to score} = \begin{cases} 7, & \text{if label is } A \\ 6, & \text{if label is } B \\ 5, & \text{if label is } C \\ 4, & \text{if label is } D \\ 3, & \text{if label is } E \\ 2, & \text{if label is } F \\ 1, & \text{if label is } G \end{cases} \tag{3.7}$$

$$\text{fraction labels} \geq \text{C} = \frac{\sum_{i=1}^{n} \mathbb{1}(S_i \geq 5)}{n} \tag{3.8}$$

$$S_{kc,epc} = \min\left(\frac{\text{fraction labels} \geq \text{C}}{\text{target}}, 1\right) \tag{3.9}$$

The EPC Labels normalization method was not used in Muscillo et al. (2021) due to the absence of KPIs related to EPC labels. This KPI was added to this research due to the municipal goal of household temperature retention related to SDGs 7.1 and 7.3. Since this KPI could not be measured using existing normalization methods, a new one had to be added. Firstly, all EPC labels were given a score of 1-7, with 1 being low (G) and 7 being high (A). Subsequently, the fraction of the labels with a score equal to or higher than a C (or score 5) was counted per district. Lastly, this fraction was compared to the SDG target of 20%, with a score capped at 1. Equation 5 is only used for ECR4.

4 Data Analysis

This chapter presents the data analysis conducted using open-source datasets. First, section 4.1 outlines the various data sources utilized in the study. Following this, the district boundaries and demographic characteristics essential for the analysis are detailed. Subsequently, the individual Key Performance Indicators (KPIs) for each district are displayed, and the steps taken to calculate the final absolute KPI scores in their appropriate units are explained.
The primary geographic boundaries for Barcelona, Spain, were obtained using the OSMnx Python library, which enables automated access to OpenStreetMap data. Specifically, the function `ox.geocode_to_gdf()` was used to extract Barcelona's geospatial boundary as a GeoDataFrame (GDF). This dataset served as the foundational layer for further analysis, focusing on district-level spatial and population data. The results of the data analysis can be found in Appendix A.

4.1. Open-source Datasets

A variety of data sources were used for calculating the different Key Performance Indicators. Barcelona benefits from an extensive open-source data network, which forms the primary basis for this report, along with supplementary data from OpenStreetMap. A comprehensive overview of all data sources is provided in Table 4.1.

Table 4.1: Sources KPIs

Area	KPI	Source
Digitalization	D1	Open Data BCN
Energy, Climate and Resources	ECR1	Open Data BCN & Energia Barcelona
	ECR2	Open Data BCN
	ECR3	Water Utility Barcelona
	ECR4	Open Data Catalunya
Mobility	M1	OpenStreetMap
	M2	Ajuntament de Barcelona
	M3	OpenStreetMap
	M4	OpenStreetMap
	M5	Open Data BCN
Waste	W1	Análisis de Eco-Eficiencia del Municipio de Barcelona
	W2	OpenStreetMap
	W3	Ajuntament de Barcelona

4.2. Districts

To link the data of the various KPIs to the districts, the polygons of the districts first needed to be retrieved. For this, the steps and data from Luna (2023) were followed. The process included the following steps:

1. The data was imported from the GitHub link mentioned on the website by Luna (2023).

2. The dataset was filtered to include only the district name and the geometry.
3. The dataset was then merged with a dataset containing the population per district.
4. This resulted in a dataset with all the districts, including the population and polygon for each district, which was exported as a GeoJSON.

This dataset is used for all the KPIs, enabling calculations such as per capita metrics and identifying polygons located within specific districts.

4.3. Digitalization

In the Digitalization area, the number of WiFi Points is the sole KPI. The dataset used to analyze this KPI, along with the specific steps taken to process the data, is detailed below. The results for the data analysis on Digitalization can be found in Table A.1.

D1: WiFi Points

The WiFi access points, or hotspots, located across various municipal amenities and public spaces in the city of Barcelona, were sourced from Open Data BCN. This dataset contains 1.049 rows, each representing an individual WiFi point, and was last modified on August 29th, 2024. All points include district information as well as longitude and latitude coordinates.

During the Exploratory Data Analysis, it was discovered that one row contained missing values across all columns. This row was deemed uninformative and was subsequently dropped to ensure data quality. After handling the missing data, the remaining dataset was cleaned further by dropping unnecessary columns, leaving only the essential information.

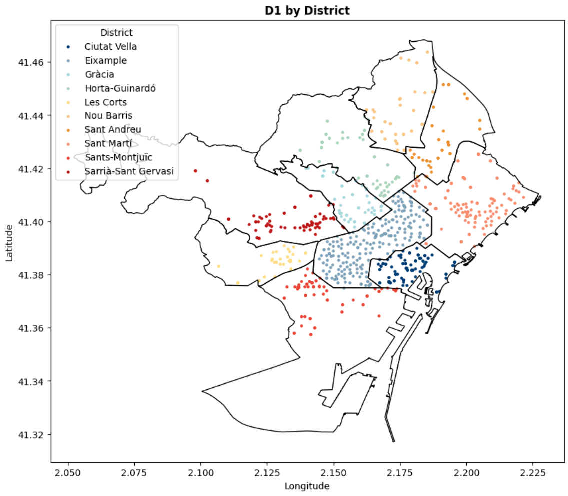


Figure 4.1: WiFi points per district

The cleaned DataFrame was then converted into a GeoDataFrame using the GeoPandas package, creating a geographic point for each WiFi hotspot based on the longitude and latitude coordinates. Using a spatial join on district boundaries, the resulting DataFrame contains all data points fall within the district boundaries of Barcelona.

A visualization of the WiFi points sorted per district is included in Figure 4.1. Using the method described in section 3.2, the percentage of households within a 10-minute walking distance to a WiFi hotspot was calculated using the Carto software, described in section 3.2.

4.4. Energy, Climate and Resources

For the Energy, Climate, and Resources area of the Circular City Index, various data sources were utilized. While most information was available through Open Data BCN, certain analyses required additional data due to gaps in the municipality's datasets. Specifically, alternative data sources were needed for ECR3 and ECR4. The details of these data sources, as well as the steps taken in the analysis, are explained in further detail below. The results for the data analysis on Energy, Climate and Resources can be found in Table A.2 and Table A.3.

ECR1: % of Local Energy Self-sufficiency (from Renewables by Municipal Buildings

From the Open Data BCN platform, the electrical energy consumption data for 2023 was extracted and aggregated per postal code in Barcelona. The accuracy of the total consumption values was cross-referenced using official datasets of "The Energy Observatory | Energia Barcelona | Ajuntament de

Barcelona", 2022 to ensure consistency and reliability. The dataset consists of 241.125 rows, detailing energy consumption per postal code, with Barcelona containing 42 distinct postal codes within its district boundaries.

Exploratory Data Analysis Energy Consumption

The dataset revealed two significant outliers in the residential energy consumption category, with values exceeding 800.000 kWh within a 6-hour period. These data points are considered unlikely to be accurate, as the consumption levels surpass even the highest outliers observed in the industrial sector. Consequently, these two data points have been excluded from the analysis to prevent distortion of the results.

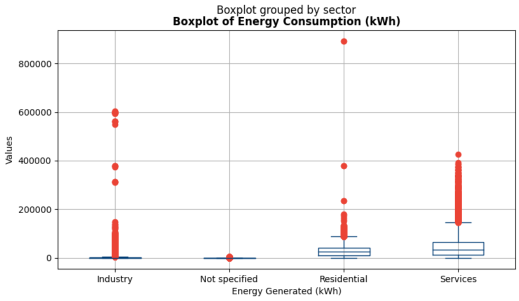


Figure 4.2: Boxplot of Energy Consumption

An analysis of high energy consumption values within the industrial and services categories was also conducted. Unlike the residential sector, the energy usage in these categories appears justified due to the presence of power plants, industrial areas, and large public services consumers in Barcelona. Furthermore, the total consumption for these sectors is consistent with the official yearly energy consumption figures reported by the Barcelona municipal government. Therefore, the outliers in the industrial and services sectors have been retained for analysis.

A boxplot that includes these outliers has been provided in Figure 4.2, along with descriptive statistics for total energy consumption in Table 4.2, both with and without outliers. This comparison highlights the effect of extreme values on the dataset.
Additionally, the dataset was thoroughly examined for duplicates, missing values, and other inconsistencies. The results confirm no missing or NaN values, and duplicates are within normal limits, ensuring the data's reliability for further analysis.

Table 4.2: Descriptive Statistics of Total Energy Consumption (ECR1)

Statistic	With Outliers (kWh)	Without Outliers (kWh)
Count	241,125	241,123
Mean	24,681.1	24,673.9
Standard Deviation	32,723.7	32,628.5
Minimum	0.0	0.0
25% Quantile	333.0	333.0
Median (50%)	12,305.0	12,304.0
75% Quantile	39,225.0	39,224.0
Maximum	891,516.0	604,699.0

Spatial Analysis of Postal Codes and City Districts

The next step involved aligning postal codes with Barcelona's districts using a GeoJSON file containing both district and postal code boundaries. This alignment is essential, as the KPI data is organized by postal code, whereas our analysis requires aggregation at the district level. To achieve this, the spatial relationship between postal codes and city districts was analyzed through geometric operations on the boundary datasets. A Python script was then executed to carry out the following steps:

1. **Re-projection:** Both the GeoDataFrames containing district data and districts with zipcodes were re-projected to EPSG:25831 to maintain spatial consistency.
2. **Intersection Calculation:** An empty list named `results` was initialized to store the intersections between postal codes and city districts. A nested loop was used to iterate over each postal code and city district, calculating the geometric intersection using the `geometry.intersection()` method.
3. **Overlap Identification:** If a valid intersection was found (i.e., the overlap was non-empty), the following information was added to the `results` list:

- Postal code identifier
- District name
- Geometry of the intersection
- Area of the intersection (in square meters), computed using the `area` attribute of the intersection geometry

4. **Creation of a GeoDataFrame:** After all intersections were identified, the `results` list was converted into a GeoDataFrame containing the postal codes, city districts, intersection geometry, and intersection areas.

Adjustment of Postal Code-District Areas Below Threshold

After calculating the intersections, some areas stood out as being only a very small percentage. This is why a threshold was introduced for areas that contributed less than 5% to the total postal code area. This step ensures that small overlaps are accounted for and re-assigned to the most contributing district for each postal code.
To adjust the areas, the following approach was applied:

1. A copy of the original intersection GeoDataFrame was created, and an empty list, `adjusted_rows`, was initialized to store the adjusted rows for each postal code.
2. For each postal code:
   - All rows corresponding to the postal code were extracted.
   - The row with the highest percentage contribution to the total postal code area was identified. This row represented the district with the largest spatial overlap.
3. If any postal code overlapped with a district for less than 5% of its area value, this area was added to the district containing the largest share of said postal code. Rows with contributions greater than or equal to 5% were retained and appended to the `adjusted_rows` list.
4. The percentage contribution for the largest district was recalculated based on the updated area. This adjustment ensures that the new distribution of areas is accurately reflected in the dataset.

Once the adjustments were complete, a new DataFrame `adjusted_rows_df` was created, containing the recalculated areas and percentages for each postal code and corresponding city district. This process ensures that postal codes with minimal overlap across multiple districts are correctly represented, with the majority of their area assigned to the most significant contributing district.

Energy Consumption Distribution per District

To analyze the distribution of Electrical Energy Consumption (EEC) across districts in Barcelona, the total electrical energy consumption per postal code was obtained from the original dataset. Each postal code's energy consumption was distributed across the districts based on the percentage area overlap, derived from the `adjusted_intersection_gdf` GeoDataFrame. The energy consumption of each district was calculated as:

$$\text{EEC}_{\text{District}} = \sum_{p \in Postalcodes} (\text{EEC}_{\text{Postal Code}} \times \frac{\%\ \text{Postal Code}_{\text{District}}}{100}) \tag{4.1}$$

The energy contributions for each district were aggregated by summing the values for all postal codes overlapping with that district. This resulted in the total energy consumption per district.

Solar Energy Generated by Municipal Buildings per District

The solar energy generated by municipal buildings is obtained from the Energia Barcelona platform. This platform provides an overview of all municipal buildings equipped with solar panels, detailing the amount of energy produced in kilowatt-hours. The dataset consists of 166 rows, each including latitude and longitude coordinates, as well as a column specifying the districts in which the municipal buildings are located.
To prepare the data for analysis, an Exploratory Data Analysis was conducted, including the following steps:

- **Missing Values**: Initially, the dataset was checked for missing values. Three entries were found to be missing both latitude and longitude coordinates. However, since the corresponding addresses were present in the DataFrame, these coordinates were manually filled in using the GPS Coordinates tool. This allowed for the creation of a complete dataset without missing values.
- **Outlier Investigation**: Outliers were also examined in the dataset, particularly with respect to energy generation values. These outliers corresponded to municipal buildings equipped with very large solar panel fields, such as large public facilities or community centers, which explains the higher energy output. As a result, these outliers were deemed valid and no further action was taken.

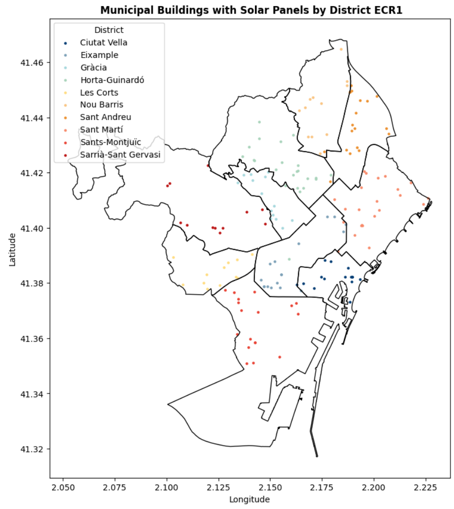


Figure 4.3: Location of Municipal Buildings with Solar Panels per Districts

With all missing values resolved and outliers accounted for, the dataset was visualized on a map to show the geographic distribution of energy-generating municipal buildings within the district borders of Barcelona. This map is presented in Figure 4.3. Each building's location is plotted within its respective district, providing a clear visual representation of solar energy generation across the city.
The final dataset was verified as reliable and within the research grid, making it suitable for further analysis. Several operations were then performed on this DataFrame to continue the analysis.

1. **Grouping the Data:** The data in the DataFrame is grouped by the unique values in the `district` column. This aggregation ensures that all rows corresponding to the same district are combined.
2. **Summing Energy Generation:** For each district, the sum of the values in the energy generation column is calculated. This operation effectively totals the energy generated for each district.
3. **Resetting the Index:** The `reset_index()` method is invoked to convert the grouped data back into a standard DataFrame format. After grouping, the original index is replaced with a new default integer index, and the grouped `district` column becomes a regular column in the resulting DataFrame.

As a result, a new DataFrame is created with two columns: `district` and the total energy generated (`energia_kwh`) for each district, with each row representing a distinct district.

Calculation of the Ratio Between Generated and Consumed Electrical Energy

The final step involves calculating the ratio between the generated and consumed electrical energy for each district. This is done by combining the resulting DataFrames from the analyses of generated and consumed electrical energy. The following formula is applied to determine the final ratio score for each district:

$$\text{Ratio} = \frac{\text{EEG}_{\text{District x}}}{\text{EEC}_{\text{District}}} \tag{4.2}$$

Where $\text{EEG}_{\text{District}}$ is the electrical energy generated in a district, and $\text{EEC}_{\text{District}}$ is the electrical energy consumed in a district.

ECR2: Air Quality

The air quality dataset from 2022 was sourced from Open Data BCN. The first step in preparing the data involved renaming the columns for clarity. Three datasets were used as input, each representing different pollutants: PM_{10}, $PM_{2.5}$, and NO_2. These datasets included both the location and pollution levels of each substance. The pollution levels were originally provided as strings, representing ranges (e.g., 20-30 µg/m^3). The highest value from each range was selected to account for the worst-case scenario. This transformation converted the pollution column into an integer type for further analysis.

The dataset did not contain missing values. Although several duplicates were identified in the pollution level data, no duplicates were found in the geographical coordinates, indicating a satisfactory level of data integrity with no immediate concerns regarding data cleanliness.

Regarding the pollution values, some outliers were detected. However, these outliers were within a plausible range based on expected pollution levels. For example, as shown in Figure 4.4, the outliers for NO_2 are slightly above the expected range but remain within the plausible upper limit of 70 µg/m^3, compared to the typical maximum of 50 µg/m^3. Therefore, the decision was made to retain these outliers, as they are more likely to represent valid extreme cases rather than faulty data.

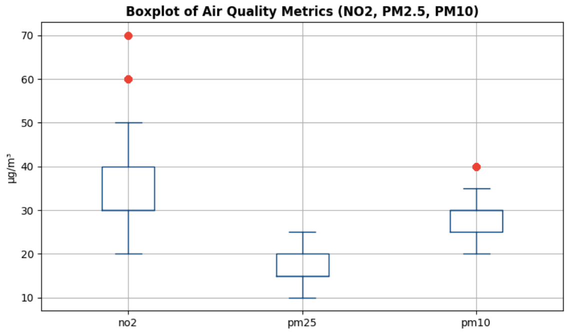


Figure 4.4: Box Plot of Air Quality in µg/m^3 (ECR2)

After spatially joining the dataset with the district boundaries, some points were assigned NaN values for the district field. Upon further inspection through plotting, it was found that all of these points fell outside the district boundaries. Consequently, these points were dropped from the dataset. The remaining data was then grouped by district, and the mean pollution levels for each pollutant were calculated. This data cleaning process resulted in a dataset that reflects the mean maximum pollution levels for each district.

ECR3: Water Efficiency

The water efficiency data is sourced from a private provider. This dataset contains information about different water sectors, their geometry, and their water usage per year in m^3. This water usage is urban water usage, so it is in line with the SDG. First, the consumption needs to be converted to liters per day. This is done by multiplying the total consumption column by 1,000 and dividing it by 365. The dataset did not contain any missing or duplicate values, and the DataTypes of all columns were already correct.

The boxplot shown in Figure 4.6, highlights some outliers in the dataset. However, since the farthest outlier is only 1.5 times the maximum, the decision was made to retain the outliers in the dataset. Another consideration is that the water sectors vary in size, so it is possible that one water sector is larger than the others. Proportionally, the water usage per inhabitant per day is also within a logical range.

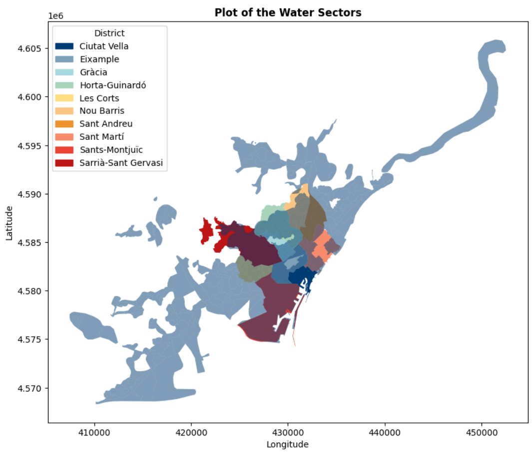


Figure 4.5: Plot of the Water Sectors

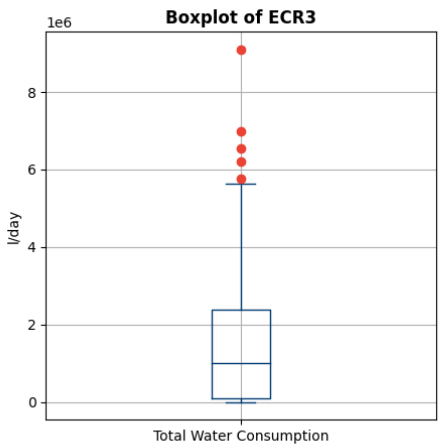


Figure 4.6: Box Plot of Water Usage in l/day (ECR3)

After conducting the exploratory data analysis, the water usage dataset needed to be converted into water usage per district. However, since the water sector boundaries are not the same as the district boundaries, adjustments to the dataset were necessary. Additionally, there was more data available than just within the borders of Barcelona, as can be seen in Figure 4.5. This needed to be filtered first, which was achieved by spatially joining the district and water GeoDataFrames. The approach for calculating the area of a water sector within a district differs slightly from the method used in ECR1. The following steps were taken:

1. The CRS (coordinate reference system) was converted into ”calculation mode” with an EPSG of 25831 instead of ”plot mode” with an EPSG of 4326.
2. The area of each water sector was calculated in m^2 and added as a column.
3. The area of each district was calculated in m^2 and added as a column.
4. Using the Geopandas function `overlay`, a new dataset was created where each row represents a part of a water sector within a district, meaning that some water sectors appear more than once. The geometry column represents the part of the water sector located in a specific district.
5. The percentage of each water sector that lies within each district was calculated by dividing the m^2 of the water area within a district by the total m^2 of the entire water sector.
6. The `weighted_consumption` in a given district was calculated by dividing the water percentage by 100 and multiplying this by the total consumption of the water sector.
7. The data was then converted back into a GeoDataFrame, and the CRS was reset to the ”plot mode” CRS of 4326.
8. The dataset was grouped by district, summing the `weighted_consumption` per district.
9. The dataset was merged with the districts dataset again to include the population data.
10. The water usage per person per district was calculated by dividing the `weighted_consumption` per district by the population of that district.
11. Finally, only the columns for district, district geometry, and water consumption (ECR3, now in l/inhab/day) were saved into a new DataFrame.

ECR4: EPC Labels

The EPC labels of households in Barcelona are sourced from the Open Data of Catalunya. This subsection describes the steps taken to clean and process the data to obtain a usable dataset.

Data Cleaning

The original dataset contains 1,346,332 rows, covering the entire region of Catalunya. To focus on the households within the province and city of Barcelona, the data is filtered by the columns `NOM_PROVINCIA` and `COMMERCA`. This ensures that only entries from the province of Barcelona and within the city limits are included.

After converting the WKT data, in the column `GEOREFERÈNCIA`, into geometrical objects, a GeoDataFrame is constructed using the GeoPandas library. Next, the boundaries of Barcelona are obtained using the OSMnx library. The function `ox.geocode_to_gdf` is used to convert the city name into a GeoDataFrame containing the geographical boundary of the city. This command retrieves the polygon geometry representing Barcelona’s outer boundary, which is essential for further spatial analysis.

To identify which households are located within the city boundaries, a spatial join is performed using the `gpd.sjoin` function from GeoPandas. This operation checks whether points (households) lie within the boundary polygon (Barcelona). The `how='inner'` argument ensures that only households within the boundary are retained, while the `op='within'` argument specifies the geometric relationship.

Next, an Exploratory Data Analysis (EDA) is conducted to further explore the data. It is found that there are many duplicates in the `GEOREFERÈNCIA` column. Upon closer inspection, these duplicates represent different apartments listed at the same address. The total number of EPC labels in the dataset is visualized in Figure 4.7. No missing values were detected, and the dataset is now ready for further cleaning.

Afterward, a spatial join is performed to assign each household to its corresponding district, using the same method as described earlier.

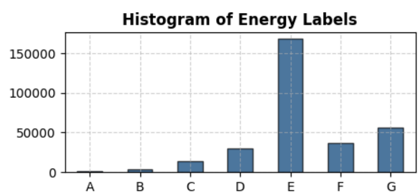


Figure 4.7: Histogram of Energy Labels

Finally, the number of households in each district is counted according to their energy label qualification. This is

achieved using the `groupby` function, which groups the data by both district and the energy label qualification field, `Qualificació de consum d'energia primaria no renovable`. The result is a count of households for each combination of district and energy label.
The household data is aggregated by district and energy label using the `groupby` function, followed by the `size()` function to count occurrences. The `reset_index()` function stores the result in a new DataFrame for further analysis.
To ensure clarity, the data is sorted first by district and then by energy label qualification. Sorting provides a clear hierarchical structure and is particularly useful when exploring the top household counts for each energy label in each district.

4.5. Mobility

For the Mobility section of the Circular City Index, a range of data sources was employed. The primary focus was on utilizing governmental data; however, in cases where this data was incomplete or unavailable, OpenStreetMap contributors (2017) (OSM) served as the secondary source. As a final measure, tertiary data sources were consulted. The specific details of these data sources, as well as the methodology applied in the analysis, are elaborated upon in the subsequent sections. The results for the data analysis on Mobility can be found in Table A.4.
section 3.2

M1: Pedestrian Area

The pedestrian-level street network was imported using data from OpenStreetMap, resulting in a directed graph of Barcelona's street network with specific filters applied to focus on pedestrian-friendly infrastructure. Following the methodology outlined in the original Circular City Index (CCI) by Muscillo et al., 2021, the following OpenStreetMap (OSM) tags were used to extract only relevant pedestrian paths:

- `place: square`
- `highway: [path, pedestrian, footway]`
- `leisure: park`
- `foot: designated`

After selecting the data from OpenStreetMap, and prior to conducting the Exploratory Data Analysis (EDA), the areas of the geometries for each row were calculated. This step ensures that the EDA can properly account for the spatial characteristics of the data under analysis. Additionally, the geometries have already been spatially joined with the corresponding districts. This results in a dataset consisting of 48,260 rows, where each row represents a pedestrian area, with columns indicating the geometry, its area, and the district in which it is located.

Exploratory Data Analysis

From the selected data described above, the results are presented in Figure 4.8. A notable observation is the presence of points, rather than the expected linestrings or polygons, which are typically associated with areas. This discrepancy is also reflected in the legend. Additionally, as shown in Table 4.3, several rows lack an assigned area.

Table 4.3: Missing Values of M1

Missing Values	Zeros	Percentage NaN
0	0	0.0%
0	46,480	0.0%
868	0	1.8%

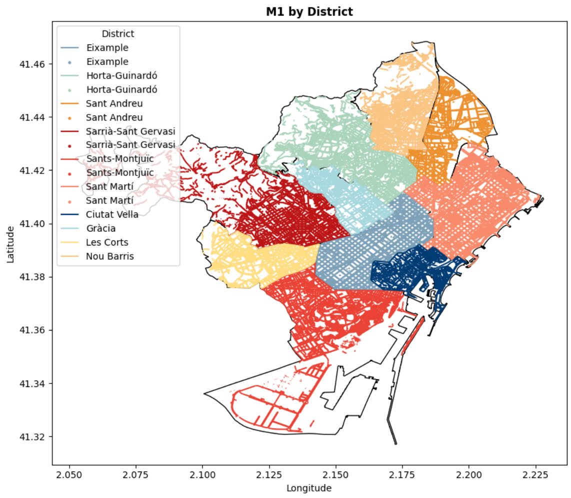


Figure 4.8: Plot of all pedestrian areas in Barcelona per District

Rows with area is zero

This presents a problem, as accepting this data would result in missing significant portions of the pedestrian network. Therefore, further investigation was conducted. In Table 4.4, the types of geometries used in the DataFrame were examined. We identified four different types: LineString, (Multi)Polygon, and Point. Each of these—LineString, Point, and (Multi)Polygon—must be interpreted differently in order to calculate the area of the pedestrian paths. Below, we describe how each type was handled:

- LineString: LineStrings represent linear features, such as pathways or narrow sidewalks. Based on information from Soto (2023), an assumed width of 2 meters is applied, reflecting the average sidewalk width in Barcelona, to calculate the approximate pedestrian area by doubling the length of each LineString.
- Polygon/MultiPolygon: Polygons (and MultiPolygons) already represent areas, such as parks or squares. In this case, the area can be directly calculated from the geometry without further assumptions.

Table 4.4: Geometry Counts of M1

Geometry Type	Count
LineString	46,464
Polygon	1,761
MultiPolygon	19
Point	16

- Points: Points represent specific locations, which are not sufficient to represent an area directly. In this case, we lacked sufficient information to accurately infer the pedestrian area that these points might represent, such as small squares or other designated pedestrian spaces. Therefore, these 16 points were excluded from the dataset to ensure the integrity and accuracy of the pedestrian area calculations.

Rows Without District

In addition to the rows with no area or where the area is zero, we also observe in the table that there are rows without an assigned district. To gain a better understanding of where this issue originates, a plot of all pedestrian areas without district assignments has been created, as shown in Figure 4.9. This visualization allows us to pinpoint the geographic locations of the missing district data and further investigate the causes of these gaps.

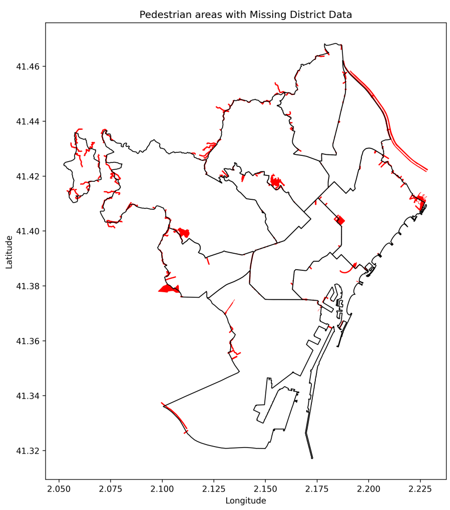


Figure 4.9: Plot of all pedestrian area in Barcelona missing District Data

As shown in Figure 4.9, all data points without a district assignment are located on district boundaries or cross multiple district borders. This suggests that the reason they are not linked to a district is due to their position at or across district lines. This issue can be resolved by using the overlay function from GeoPandas, which enables the precise calculation of the area within each district. For points that cross multiple districts, the exact square meters within each district can be calculated, ensuring accurate attribution of pedestrian areas to the relevant districts.

Final Data

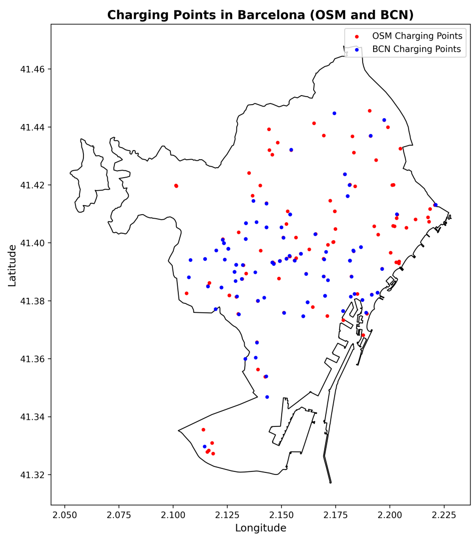
This process results in a clean DataFrame where the square meters for all pedestrian areas have been calculated. The DataFrame is grouped by district, and the areas are summed accordingly. Afterward, this DataFrame is merged with the one containing the demographic characteristics of the districts. This merge enabled the calculation of the metric of M1: area per 100 inhabitants per district, which is calculated as:

$$\text{Area per 100 inhabitants} = \left(\frac{\text{Total pedestrian area}}{\text{Population of the district}}\right) \times 100 \tag{4.3}$$

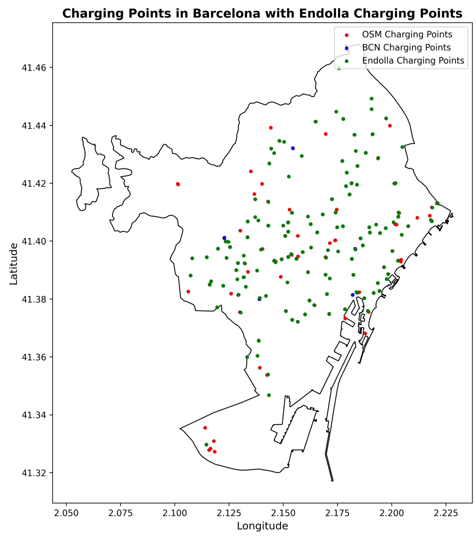
M2: Charging Stations

According to various sources (e.g., ElectroMaps (2024) and Plug (2016)), Barcelona has over 500 charging stations. Based on these sources, the decision was made not to use data from the Ajuntament or Open Data BCN, nor from OSM, but instead to rely on a tertiary source, for the following reasons.

Both of the aforementioned datasets contain far too few data points, as shown in the table. Furthermore, when the data points from these datasets are plotted side by side, there appears to be very little overlap between them. For this reason, a third-party dataset was sought, and this dataset was overlaid onto the other datasets in the figure. It is evident from this overlay that the third dataset encompasses a significant portion of both original datasets. Additionally, this third dataset contains ”count” rows, which led to the decision to proceed with the E. Barcelona (2024) dataset for further analysis.



(a) OSM and BCN data for Charging Points



(b) OSM, BCN and Endolla data for Charging Points

Figure 4.10: Comparison of datasets of Charging Points

Table 4.5: Count and Unique Geometries of Charging Points and Other Data in Barcelona

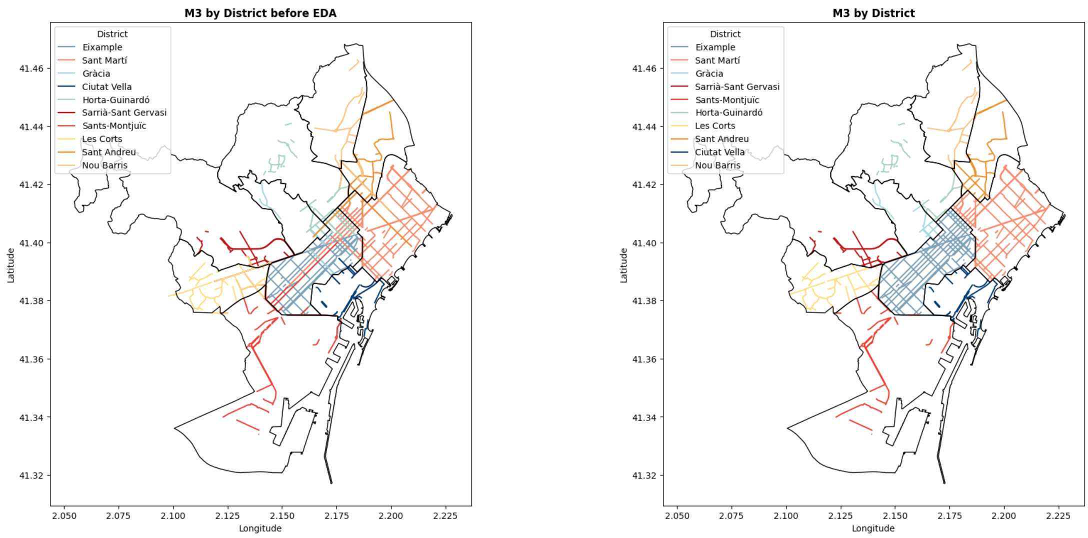
Data Source	Count	Unique Geometries
OSM Charging Points	113	113
BCN Charging Points	393	75
Endolla Charging Points	1640	136

Data Cleaning

The code begins by performing a spatial join between the GeoDataFrame of the Charging Points and the GeoDataFrame of district geometries, where the spatial relationship is defined using the predicate ”within.” This spatial join matches geometries from charging stations with their corresponding districts. Because many geometries of charging stations appear multiple times, it is assumed that each duplicate geometry corresponds to multiple charging spots located at the same physical location, such as at a single charging station. To quantify this, the code counts how many times each unique geometry appears in the DataFrame. A new DataFrame is then created, containing two columns: one for the unique geometries and another representing the number of times each geometry is duplicated, which serves as a proxy for the ”capacity” of each charging station. Finally, this new DataFrame is converted into a GeoDataFrame (M2), preserving the spatial information for further geospatial analysis.

M3: Cycleway Length

For the analysis of cycleways, data was sourced from the Ajuntament de Barcelona, as this source provides a detailed dataset containing the geometries of all bike lanes within the city. The bike lane geometries are represented as linestrings, which enables the precise calculation of their lengths. This is consistent with the unit of measurement used in M3. The length of each bike lane was calculated for every row in the dataset. Following this, each bike lane was assigned to its respective district through a spatial join with the districts GeoDataFrame. The resulting GeoDataFrame includes the geometries, the lengths (in meters), and the corresponding district for each bike lane in Barcelona. This approach ensures that the dataset is both comprehensive and spatially accurate for further analysis.



(a) Cycleways in Barcelona before cleaning data **(b)** Cycleways in Barcelona with corrected data

Figure 4.11: Comparison of datasets of cycleways

The aforementioned dataset was subsequently plotted on a map of Barcelona, as shown in Figure 4.11a. In this plot, it becomes evident that the bike lanes are not correctly linked to their respective districts, as the colors of the bike lanes do not align perfectly with the districts. The reason for this, similar to the issue encountered with M1, is that many bike lanes cross multiple district boundaries. To resolve this, the same method was applied: using the intersect function, the bike lanes were split at district boundaries, ensuring that each segment is accurately assigned to the correct district, shown in Figure 4.11b.

Data Cleaning

To transform the data into the correct units for M3, the total length of bike lanes for each district is calculated. This is done by grouping the data by district and summing the lengths of bike lanes (in meters). The lengths are then converted from meters to kilometers. Next, the geometries of the districts are processed to calculate the area of each district. The area of each district is calculated in square meters and converted to square kilometers. Following this, the DataFrame with bike lane lengths is merged with the district area to create a unified dataset which includes both the length of bike lanes and the area of each district. The bike lane density (denoted as m3) is then calculated by dividing the total length of bike lanes in kilometers by the area of the district in square kilometers. This ratio represents the density of bike lanes per district, which is rounded to three decimal places. Finally, the M3 DataFrame is created, containing only the district names and the corresponding bike lane density (m3), ready for further analysis.

M4: Transit Stops

Transit Stops data for Barcelona was collected from OpenStreetMap contributors, 2017 (OSM). The dataset includes various types of public transport infrastructure within the city, such as bus stops, tram stops, subway stations, and railway stations. The OSM tags were filtered to extract only the relevant geometries and attributes, following a methodology similar to the one outlined in the original Circular City Index (CCI) by Muscillo et al., 2021.
The following OpenStreetMap (OSM) tags were used to collect data on Transit Stops:

- `highway: bus_stop` For bus stops
- `railway: station` For railway stations
- `station: subway` For subway stations
- `railway: tram_stop` For tram stops

The data was filtered to include only relevant columns, such as name, geometry, highway, tram, railway, and station, ensuring a focused dataset for further analysis. This dataset provides a comprehensive overview of Transit Stops throughout Barcelona, capturing multiple modes of transport across the city.

Subsequently, a spatial join was performed with the district boundaries, allowing each public transport stop to be assigned to the district in which it is located. This process ensures that every public transport point, regardless of type (bus, tram, metro, train), is accurately linked to its corresponding district. The result is a comprehensive DataFrame containing all types of Transit Stops along with their associated districts, providing a detailed overview of the public transport distribution across Barcelona. This distribution is illustrated in Figure 4.12, where the spatial arrangement of Transit Stops across the city's districts is clearly visible.

Subsequently, various conditions are applied to assign transport types based on the content of several columns. Rows where the highway column is not null are classified as `bus_stop`, while rows with `yes` in the tram column are assigned the type `tram`. Similarly, those with `tram_stop` in the same column are also assigned the type `tram`. For the subway category, rows with `subway` in the station column are marked as such. In Table 4.6 the counts for all categories are presented

Table 4.6: Transport Type Distribution for M4

Transport Type	Count
Bus Stop	2501
Subway	131
Tram	60

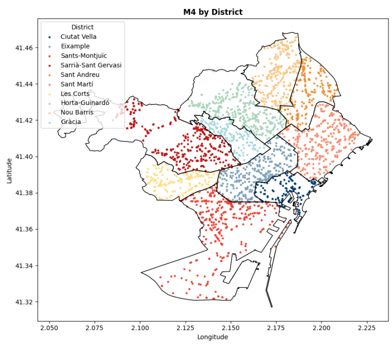


Figure 4.12: Transit Stops in Barcelona

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Based on data from Transport Metropolitans de Barcelona (2015) corporate information, Barcelona has a total of 2,623 bus stops and 165 subway stations. Subsequently, Trenscat (2021) includes 56 tram stops across different routes. The comparison of the manually identified tram stops (56) with the reported 60 tram stops in Table 4.6 suggests a minor discrepancy. Similarly, the number of bus stops and subway stations (2,501 bus stops and 131 subway stations) is slightly lower than the official figures provided by TMB. This difference highlights a limitation in the dataset, likely due to variations in the completeness OpenStreetMap versus official TMB data. Such inconsistencies emphasize the need for caution when interpreting results.

M5: Bike-sharing Points

For the bike-sharing data, information was sourced from Open Data BCN, which was downloaded directly from the Open Data BCN website.
The dataset was first inspected using df.head(). Relevant columns, including station id, capacity, latitude, and longitude, were selected and stored in a new DataFrame. This data was then transformed into a GeoDataFrame using geopandas, where the lat and lon columns were converted into geometric points. Afterward, unnecessary columns were dropped to simplify the dataset.

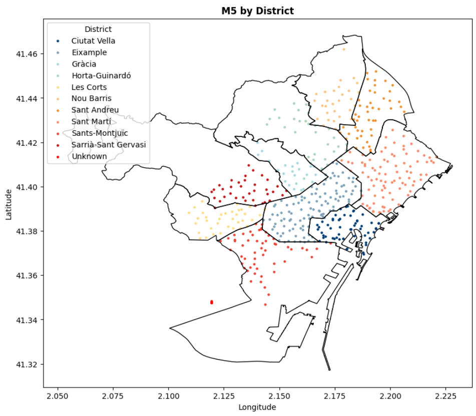

Figure 4.13: Bicing Stations in Barcelona

Next, duplicate geometries were removed to ensure unique station locations, as only the Bicing locations will be analysed, and not the capacity. To spatially link the bike-sharing stations with their respective districts, a spatial join was performed with the district GeoJSON. The how="left" and predicate="within" parameters ensured that each bike-sharing station was associated with the district in which it is located.
Figure 4.13 visualizes the spatial distribution of bike-sharing stations across the districts, providing a clear geographical overview of the dataset. The figure shows that some data points are located outside the boundaries of Barcelona and have not been assigned a district. These points can be dropped, as they fall outside the scope of this study and are not relevant to the analysis.

4.6. Waste

Waste management is a critical component of the Circular City Index (CCI). For the KPIs related to waste management in Barcelona, multiple datasets and reports from the municipality, as well as OpenStreetMap, were used to assess various aspects of waste generation, recycling, and e-waste collection. The results for the data analysis on Waste can be found in Table A.5.

W1: Waste Production

The data on waste production per inhabitant per day was sourced from the report by Zheng, 2019. Although the data was already organized by district, it was initially recorded in tons of waste produced per year. To convert this into kilograms per inhabitant per day, the values in tons were first multiplied by $1,000$ (to convert to kilograms), then divided by the population of each district, and finally divided by 365 (to calculate the daily value).

This process began by merging the district-level dataset, which contains district names, population data, and polygons, with the dataset on annual waste production per district. Once the data was combined, the conversion calculation was applied, and the results were stored as the W1 indicator in a new DataFrame for each district.

W2: Waste Recycling

Since there was no available dataset on the percentage of solid waste being recycled, a dataset from OpenStreetMap was used to locate all the recycling bins. This dataset includes information such as the location and type of recycling. There were two types of recycling facilities: containers and centers. However, since the recycling type "center" refers to the Green Points (the e-waste collection points) covered in W3, the dataset was first filtered to include only the recycling type "container." After filtering, only the latitude and longitude were considered, as the KPI focuses on walking distance to recycling bins.

The descriptive statistics of the data appeared correct, as the latitude and longitude values were within the expected range. Nevertheless, the histogram revealed a slight outlier around 41.32. Upon reviewing this location on Google Maps, it was found that these coordinates are outside the borders of Barcelona, indicating the presence of points located beyond the city's boundaries. There were no missing values, no duplicate coordinates, and the data types were correct.

The next step was data cleaning. After the exploratory data analysis (EDA) revealed points outside of Barcelona's borders, a spatial join was performed between the W2 dataset and the district boundaries, based on whether the recycling points were within the city limits. To ensure that the excluded points were indeed outside of Barcelona, they were plotted, as shown in Figure 4.14. These points were then removed from the dataset. In Figure 4.15, the recycling points per district can be seen.

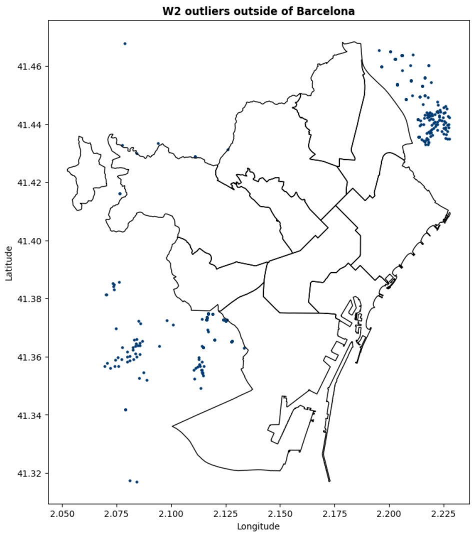

Figure 4.14: Plot of the Outliers outside of Barcelona

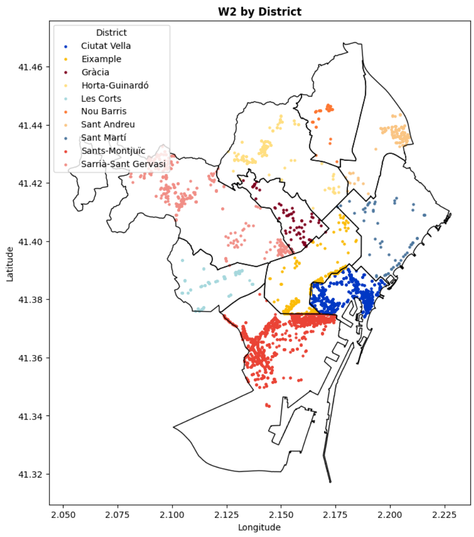

Figure 4.15: Recycling Points per District

W3: e-Waste Collection

The data for the collection of e-waste points, referred to as Green Points, was sourced from the website of Ajuntament de Barcelona. It was decided not to distinguish between the different types of Green Points (neighborhood, area, and mobile), as they all collect the same types of waste. The latitude and longitude values appeared to be within the expected range for Barcelona based on the descriptive statistics.

There were 13 missing values for the longitude and latitude. After verifying the names of these Green Points using Google Maps, it was confirmed that all of these points were located outside the boundaries of Barcelona. Consequently, the rows with missing values were removed. No duplicates were found, and the data types were correct. Figure 4.16 shows the spatial distribution of the Green Points across the districts.

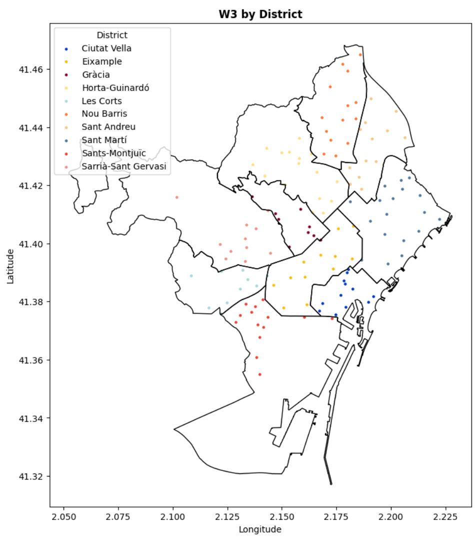

Figure 4.16: Green Points per District

4.7. KPIs for Household Access Based on Walking Distance

The KPIs M2, M4, M5, D1, W2, and W3, as previously discussed, are expressed in a specific unit: the percentage of households that can reach a particular point within a given number of minutes on foot. For example, in the case of M2, this represents the percentage of households in a district that can walk to a charging station within X minutes. To calculate these units, several specialized analytical steps were undertaken.

The first step involved gathering and cleaning the data, as detailed in the earlier subsections. The subsequent step required processing the data using Carto, which is explained in section 3.2. The output from Carto is a DataFrame with columns for district, latitude, longitude, geometry, and Carto-specific metadata. Rows are associated with polygons representing pedestrian isochrones. The data provides a spatial representation of accessibility within each district.

Further steps are required to convert this data into the correct units, which will be explained in the following sections.

Data Preparation and Household Distribution by District

To accurately determine the key performance indicators (KPIs) that represent the percentage of households within a district located within a certain walking distance from a KPI point, it is first necessary to establish the number of households in each district. This information cannot be directly extracted from the district dataset, as the dataset is based on grids of 100x100 meters, many of which intersect multiple districts. As a result, it is necessary to estimate the proportion of households within each grid that lies in each intersecting district. The following process was undertaken to derive this estimate.

At the beginning of the analysis, households located outside the districts of Barcelona are removed using a spatial join. The intersects method is applied to retain only those households that are within or intersect the outer boundary of Barcelona. Following this spatial filtering, the data is further refined by selecting only 100x100 meter grid cells that contain more than zero households (`n_fincas > 0`). These steps ensure that only relevant household data within the boundaries of Barcelona are included in the subsequent analysis.

This DataFrame is exported as a CSV file to facilitate visualizations of all households in Barcelona using the Carto platform. To calculate the surface areas of the grid cells, a new column is created to store the area values in square meters (Area m^2). Subsequently, a spatial join is performed between the household data and the district boundaries, using the within predicate to ensure that only grid cells entirely contained within a district are included.

Next, the analysis identifies districts that are located within Barcelona but were not captured in the previous within spatial join. These districts contain grid cells that span multiple district boundaries. These grids are stored in a new DataFrame, representing households that cross district borders.

At this stage of the analysis, two DataFrames are established: one containing households that are entirely within a district, and another with households that span multiple districts. The next step involves a spatial join on the DataFrame containing households crossing district boundaries, using the intersects predicate. This process results in a dataset where some grid cells appear multiple times, each associated with different districts. The dataset thus reveals all districts intersected by each grid.

Subsequently, the area of each district is calculated in the district DataFrame. The grid areas are then recalculated in the new DataFrame containing the intersecting grids, allowing for an accurate determination of the portion of each grid that falls within each district.
Following this, the percentage of the grid area within each district is calculated by dividing the grid area within a specific district by the total grid area, then multiplying by 100. This percentage is crucial for calculating weighted households, which are determined by multiplying the percentage of the grid's area within a district by the number of households in that grid. This calculation ensures that households are proportionally allocated to the appropriate districts based on the grid's geographic overlap.

At this point, the resulting DataFrame provides the number of households per grid within each district. This DataFrame is merged with the earlier dataset containing households entirely located within districts. After the merge, it becomes evident that the total number of weighted households is less than the sum from the initial dataset. This reduction occurs because some grids extend beyond the boundaries of Barcelona, leading to the exclusion of households outside the city's limits.

Finally, the data is grouped by district, and the total number of weighted households is summed for each district. This process produces a final DataFrame that accurately reflects the number of households per district, accounting for both households fully within a district and those that span multiple districts.

Walking Distance Accessibility Analysis and Final Output

This section outlines the process of analyzing and processing data to calculate the percentage of households within walking distance of specific points of interest, such as Wi-Fi Points. For this process multiple datasets are needed, including household data (from section 4.7, walkability data (from Carto), and district boundary information. The household and walkability data are transformed into GeoDataFrames, converting latitude and longitude coordinates into geometries suitable for spatial analysis.

Unnecessary columns are removed to streamline the datasets for further analysis. The core analysis involves performing a spatial join between the household data and the walkability data. This operation identifies which households are located within the walking distance of specific points of interest. The spatial join, however, introduces duplicate rows, as some households fall within multiple walkable areas. To address this, duplicates are filtered out to ensure that each household is only counted once for each district and geometry. Once the duplicates are resolved, the data is grouped by district, and the total number of households within walking distance is calculated. This figure is then compared to the total number of households in each district to compute the percentage of households that meet the walking distance criteria.

The resulting data, which contains the percentage of households within walking distance for each district, is merged with the district boundary data to assign geographical coordinates to each district. The final output is a dataset that provides spatial insights into household accessibility, with percentages indicating how many households in each district are within walking distance of the points of interest.

Finally, the processed data is saved as a CSV file to preserve the results for further analysis or reporting. This workflow provides a detailed spatial analysis of household accessibility, combining demographic data with geographic proximity in a reproducible and structured manner.

5
Sensitivity Analysis

To calculate the Circular City Index (CCI), various weights are used. First, the weights of the areas (Digitalization, Waste, Energy, Climate, and Resources (ECR), and Mobility) are considered. Second, the weights of the KPIs within these areas are applied. All these weights are derived from literature and previous research, as described in chapter 3. However, there is always an inherent uncertainty when determining such weights in a weighted scoring model, as the CCI calculation. In this chapter, a sensitivity analysis (SA) is performed on the weights of the different areas and KPIs to assess how variations in these weights impact the ranking of districts based on their CCI scores.

5.1. Method

The approach to evaluating the impact of weight determination on CCI scores uses Dirichlet-based sampling combined with sensitivity analysis. Weight variations of 10% and 50% were applied, as larger deviations were considered unreasonable based on prior research, the SDGs, and the municipality's priorities. A key constraint is that the sum of area weights must equal 1, and similarly, the sum of KPI weights within each area must also equal 1.

Dirichlet sampling is a method derived from the Dirichlet distribution, commonly used in Bayesian statistics and machine learning for generating probabilities or normalized weights that must sum to 1 Gelman et al. (2014). This method is ideal for modeling proportions across multiple categories, where the total sum must be constrained—such as weights for area and KPI scores. The Dirichlet distribution, a multivariate generalization of the Beta distribution, is particularly useful when dependencies between categories must be preserved Murphy (2012).

In this case, Dirichlet sampling is applied to generate sets of weights that meet the sum-to-1 requirement for normalized weights, which is essential for maintaining the integrity of the CCI score calculation. It ensures that the sum of the weights remains constant while allowing flexibility to explore different configurations within specified variation limits ($\pm$10% or $\pm$50%). By applying Dirichlet sampling, the sensitivity analysis can examine how varying the weight distributions impacts the CCI scores, ensuring that all weights remain within realistic bounds while preserving the model's constraints.

This process generated a new dataset with 1,000 samples for each variation. For each sample, the CCI was recalculated using the standard method outlined in chapter 3, with the KPI scores normalized from the available data. The only difference between these recalculations was the variation in the weights.

To assess the effect of weight variations on the district rankings, a ranking system was implemented. This system compared the rank (with 1 being the best and 10 being the worst) of each district across the different samples. The more a district's rank fluctuated across the samples, the greater the impact of weight variations on its CCI score. This method provides valuable insight into how sensitive the district rankings are to changes in the underlying weight allocations.

5.2. Results

Sarrià-Sant Gervasi consistently ranks last with minimal rank range, as shown in Table 5.1 and Table 5.2, indicating stability in its lower position. Sant Martí holds a stable first position in both tables, with no rank variation under the 0.1 variation and only a minor range (1 to 3) under the 0.5 variation, as seen in Table 5.1, suggesting its CCI score remains largely unaffected by weight changes.

In contrast, districts like Eixample, Sants-Montjuïc, Ciutat Vella, Gràcia, and Sant Andreu display more variability, especially under the 0.5 variation. Eixample and Citut Vella show a wide rank range (1 to 10), and Sants-Monjuïc varies from 1 to 8, indicating greater sensitivity to changes in area and KPI weights, as shown in Table 5.2.

Table 5.1: Sensitivity Analysis on Weights with 0.1 variation

District	mean_rank	std_rank	min_rank	max_rank	rank_range
Ciutat Vella	5.84	0.65	5	7	2
Eixample	4.01	0.15	3	5	2
Gràcia	5.37	0.58	4	7	3
Horta-Guinardó	2.83	0.39	2	4	2
Les Corts	7.52	0.50	7	8	1
Nou Barris	7.31	0.95	5	9	4
Sant Andreu	2.18	0.38	2	3	1
Sant Martí	1.00	0.00	1	1	0
Sants-Montjuïc	8.94	0.24	8	9	1
Sarrià-Sant Gervasi	10.00	0.00	10	10	0

Table 5.2: Sensitivity Analysis on Weights with 0.5 variation

District	mean_rank	std_rank	min_rank	max_rank	rank_range
Ciutat Vella	5.86	2.12	1	10	9
Eixample	4.60	1.86	1	10	9
Gràcia	5.45	1.69	1	8	7
Horta-Guinardó	3.50	1.61	2	8	6
Les Corts	6.92	1.39	2	9	7
Nou Barris	6.84	2.18	4	10	6
Sant Andreu	3.27	1.58	2	9	7
Sant Martí	1.02	0.15	1	3	2
Sants-Montjuïc	7.84	1.63	2	10	8
Sarrià-Sant Gervasi	9.71	0.50	8	10	2

5.3. Conclusion

From the sensitivity analysis, it can be concluded that districts that score either the highest or lowest on the Circular City Index (CCI) tend to remain stable in those positions. This can be explained by the fact that districts performing consistently well or poorly across most areas and KPIs do not experience large rank changes, even when the importance (weights) of certain areas is adjusted. Their performance is not disproportionately dependent on any single area or KPI, so when the weights are varied, their overall CCI score—and, consequently, their rank—remains relatively stable. This stability at the extremes is reflected in the lower standard deviations observed for these districts.

Interestingly, it is observed that middle-ranked districts (with mean ranks around 5) do not necessarily exhibit the highest standard deviations, as one might expect. High standard deviations indicate that the distribution of weights significantly influences the ranking. This suggests that a district with a high standard deviation likely performs very well in certain areas but poorly in others. As a result, the variation in rank across the samples, where weights are perturbed, is substantial. In other words, the areas or KPIs may contribute unequally to the district's CCI score. For middle-ranked districts, a change in the weight of certain KPIs could lead to more variability in their rankings, resulting in higher standard deviations.
From this analysis, we can conclude the following:

1. Sant Martí, the district with the highest mean ranks represent the best performer, on the CCI, as determined by this study. This district is consistently ranked at the top, even when the weights are varied, meaning the district scores good on all areas.
2. Sarrià-Sant Gervasi, the district with the lowest mean ranks represent the worst performer, on the CCI, as determined by this study. This district is consistently ranked at the bottom, even when the weights are varied, meaning the district scores bad on all areas.
3. Districts with the highest standard deviations in their rankings exhibit the greatest disparity in their performance across different areas. Improving performance in a single area could significantly enhance their overall CCI score, indicating that they are particularly sensitive to how the weights of specific KPIs are allocated. Example of districts with high standard deviations are Ciutat Vella, Nou Barris and Eixample.

6
Results

Following the data adn sensitivity analysis, the results for each district have been calculated. This chapter presents the findings in a structured progression from data analysis through to comprehensive CCI scores. First, the absolute values of individual KPIs, which serve as the basis for CCI calculation, are provided in **??**. The chapter then begins with an overview of KPI normalization, followed by a detailed examination of area scores, and concludes with the CCI scores per district.

6.1. Normalized KPI Scores

The first step in evaluating the performance of each district was to normalize the Key Performance Indicators (KPIs), which serve as the foundation for calculating the area scores and the overall Circular City Index (CCI). Tables 6.1 and 6.2 provide an overview of the normalized scores for each KPI, highlighting the variation across districts.

Observations Across KPIs

Certain KPIs reveal the most significant disparities across districts:

- Local energy self-sufficiency (ECR1) shows notable variability, with districts like Nou Barris, Horta-Guinardó, and Sant Martí scoring 1.00, while Sarrià-Sant Gervasi and Sants-Montjuïc score significantly lower at 0.09 and 0.00, respectively.
- Pedestrian area (M1) also presents a marked difference. While districts like Ciutat Vella, Les Corts, and Sant Martí score a perfect 1.00, Eixample lags behind with a score of 0.40, indicating that the latter has less pedestrian-friendly infrastructure.
- Public transport options (M4) show full scores (1.00) for all districts, which demonstrates an overall strong commitment to public transportation access across Barcelona.
- WiFi points (D1), Water efficiency (ECR3), Bicycle sharing points(M5) and Collection of e-Waste (W3) also have an overall high score over the districts.

Table 6.1: Normalized KPIs (Part 1)

District	D1	ECR1	ECR2	ECR3	ECR4	M1	M2	M3	M4	M5
Ciutat Vella	1.00	0.56	0.77	0.74	0.29	1.00	0.68	0.70	1.00	1.00
Eixample	1.00	0.52	0.69	1.00	0.38	0.40	0.69	1.00	1.00	1.00
Gràcia	1.00	0.20	0.79	1.00	0.29	0.68	0.58	0.43	1.00	1.00
Horta-Guinardó	1.00	1.00	0.78	1.00	0.23	0.97	0.34	0.22	1.00	1.00
Les Corts	0.85	0.34	0.79	0.70	0.34	1.00	0.61	0.68	1.00	1.00
Nou Barris	0.95	1.00	0.80	1.00	0.20	0.78	0.33	0.29	1.00	0.96
Sant Andreu	1.00	0.99	0.78	1.00	0.28	0.64	0.64	0.61	1.00	1.00
Sant Martí	1.00	1.00	0.75	1.00	0.31	1.00	0.36	1.00	1.00	1.00
Sants-Montjuïc	1.00	0.00	0.78	0.78	0.24	1.00	0.38	0.22	1.00	1.00
Sarrià-Sant Gervasi	0.83	0.09	0.80	0.77	0.36	0.91	0.53	0.17	1.00	0.83

Table 6.2: Normalized KPIs (Part 2)

District	W1	W2	W3
Ciutat Vella	0.53	1.00	1.00
Eixample	0.69	1.00	1.00
Gràcia	0.99	1.00	1.00
Horta-Guinardó	1.00	0.84	1.00
Les Corts	0.78	0.93	1.00
Nou Barris	1.00	0.46	1.00
Sant Andreu	1.00	0.68	1.00
Sant Martí	1.00	0.88	1.00
Sants-Montjuïc	1.00	1.00	1.00
Sarrià-Sant Gervasi	0.79	1.00	0.96

6.2. Area Scores per District

Figure 6.1 illustrates the area scores for each district based on the four areas: Digitalization (D), Energy Circularity and Resilience (ECR), Mobility (M), and Waste Management (W). Each area score is normalized and provides insight into the strengths and weaknesses of each district. Below are the most notable patterns observed from the area scores.

Digitalization (D)

All districts perform consistently well in Digitalization, Keep in mind that since Digitalization is based only on the specific KPI WiFi points, the area score for Digitalization is similar to the score before.

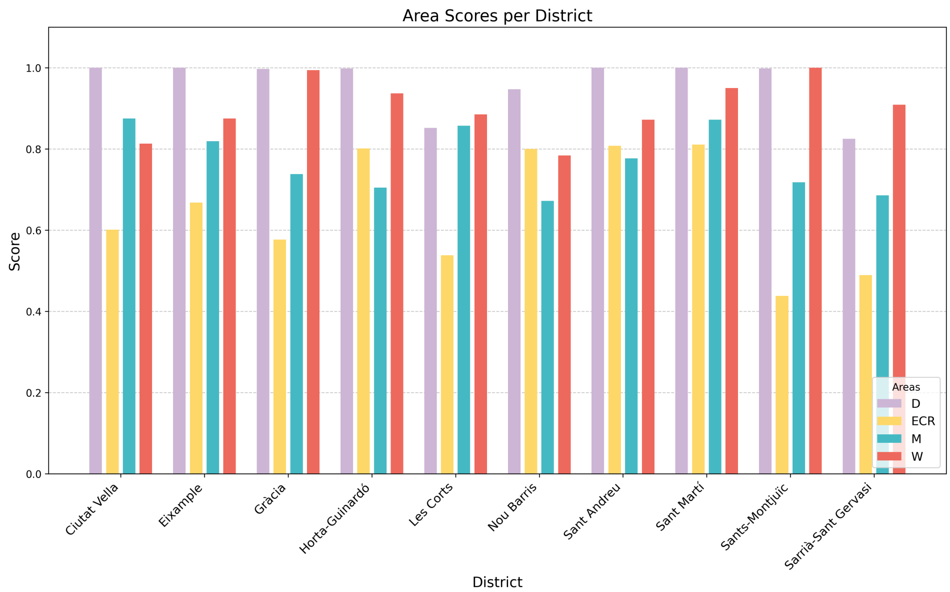

Figure 6.1: Area Scores per District

Energy Circularity and Resilience (ECR)

Energy Circularity and Resilience scores show greater variability across districts. Horta-Guinardó, Nou Barris, Sant Andreu, and Sant Martí all achieve the highest scores, close to or equal to 0.8, showing better air quality and self sufficiency than other districts.
In contrast, districts like Sants-Montjuïc and Sarrià-Sant Gervasi show lower ECR scores, close to 0.4.

Mobility (M)

Ciutat Vella, Eixample, Les Corts and Sant Martí, all perform very well in Mobility, with all scores higher than 0.8, showing that the mobility infrastructure is more user friendly.
On the other hand, the remaining districts score close to or equal to 0.7.

Waste Management (W)

A majority of the districts show near-optimal performance in Waste Management, with, Gràcia and Sants-Montjuïc reaching close to the maximum score of 1.0, which shows that the spatial planning regarding waste management is near perfect.
In contrast, districts like Ciutat Vella and Sant Andreu show lower W scores, close to 0.8.

6.2.1. Key Observations

- Sant Martí and Sant Andreu are among the districts performing well across all areas with all scores above 0.8.
- In contrary to this, Les Corts, Nou Barris and Sarrià-Sant Gervasi show some of the lowest scores across the board, with their highest score close to 0.9.
- Looking at the KPI's themselves, the Energy, Climate and Resources is the area with the lowest average score, while the Digitalization area has the highest average score. Finally, for the Waste area score, all districts scored relatively high compared to the areas ECR and Mobility, with several districts obtaining score of over 0.9. The exact scores of each area can be found in Table 6.3.

6.3. CCI Scores

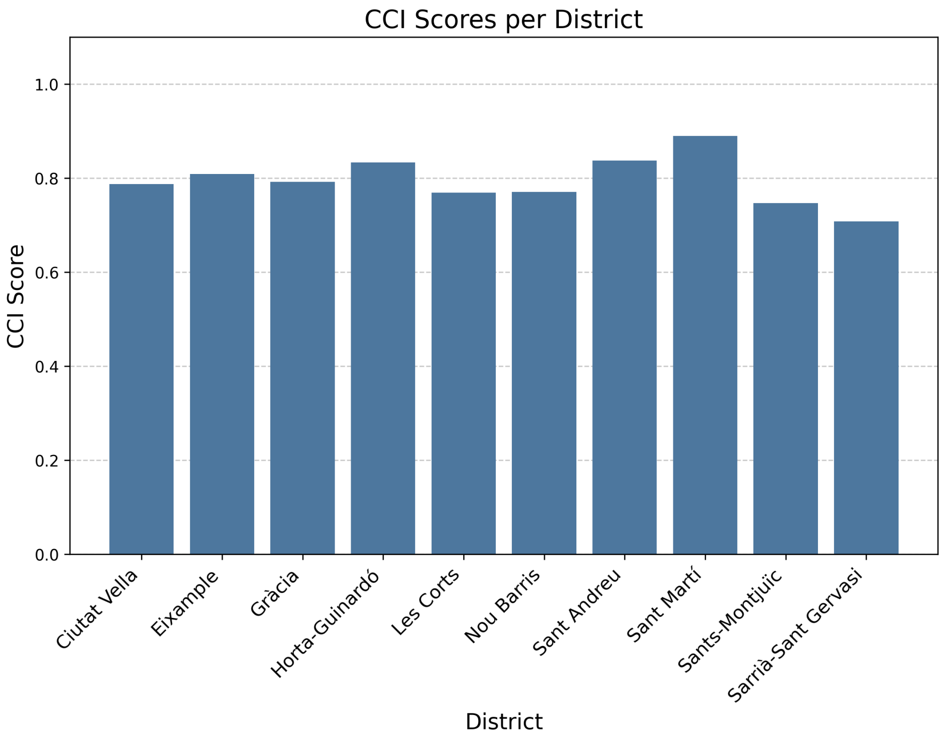

Figure 6.2: CCI Scores per District

Having discussed the separate area scores in Figure 6.1, the cumulative CCI score of these areas can be seen in Figure 6.2. While most districts fluctuate around similar values, Sant Andreu, Horta Guinardó and especially Sant Martí score higher than other districts, with a scores higher than 0.8. On the contrary to this, Sarrià-Sant Gervasi scores significantly lower than other districts, with a CCI score of 0.71.

Table 6.3: CCI Data

District	Digitalization	Energy, Climate & Resources	Mobility	Waste	CCI
Ciutat Vella	1.00	0.60	0.88	0.81	0.79
Eixample	1.00	0.67	0.82	0.88	0.81
Gràcia	1.00	0.58	0.74	0.99	0.79
Horta-Guinardó	1.00	0.80	0.71	0.94	0.83
Les Corts	0.85	0.54	0.86	0.89	0.77
Nou Barris	0.95	0.80	0.67	0.78	0.77
Sant Andreu	1.00	0.81	0.78	0.87	0.84
Sant Martí	1.00	0.81	0.87	0.95	0.89
Sants-Montjuïc	1.00	0.44	0.72	1.00	0.75
Sarrià-Sant Gervasi	0.83	0.49	0.69	0.91	0.71
Average	0.96	0.65	0.77	0.90	0.80

As a result of this research, a short interactive website was presented to the municipality of Barcelona. This website has been provided as an openly accessible source of information through the vCity platform. The link to this platform and the presentation can be found in Appendix X.

6.4. Correlation

As seen in Figure 6.3, some of the normalized scores of the KPIs correlate with each other. The high correlations (> +/- 0.7) were considered.

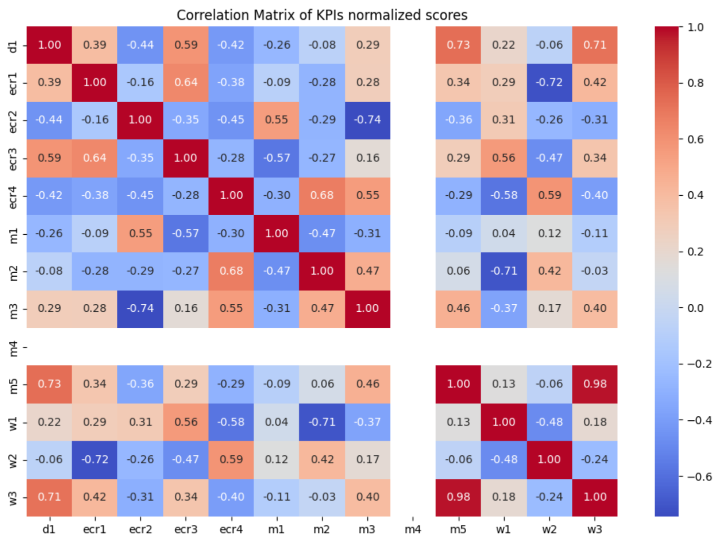

Figure 6.3: Correlation Matrix of KPI's Normalized Scores

M3: Cycleway length & ECR2: Air Quality (-0.74)

The data shows a negative correlation, which suggests that districts with more extensive cycleways tend to have poorer air quality. This may be because cycle lanes are often implemented in high-traffic urban areas, where vehicle emissions remain high despite efforts to promote cycling. On the other hand, areas with fewer cycleways might exhibit better air quality due to lower traffic levels. This finding requires further investigation to understand the underlying causes and explore whether other factors influence this relationship in Barcelona.

W1: Waste Production & ECR1: Energy Self-Sufficiency (-0.72)

The negative correlation between waste production per inhabitant and the percentage of local energy self-sufficiency of municipal buildings could be related to an indirect relationship. Waste production, measured at the residential level, and energy self-sufficiency, which pertains to municipal infrastructure, operate in separate domains, and this correlation does not have to indicate a direct causal relationship. It might suggest, however, that districts with higher waste generation might have less investment in sustainable municipal energy practices, but this warrants further investigation. There is no clear, logical connection between these variables, and additional research is required to explore potential demographic or infrastructural factors driving this association.

W1: Waste Production & M2: Charging Stations (-0.71)

Districts with higher per capita waste production tend to have fewer electric vehicle charging stations. This correlation may reflect broader demographic or socio-economic trends. For instance, districts that are more environmentally conscious, as indicated by lower waste production, may also be more likely to adopt electric vehicles, prompting the municipality to invest in more charging stations in these areas. However, the relationship may not be directly causal and could be influenced by external factors, such as income levels, environmental awareness, and urban planning priorities. Further demographic analysis could shed more light on this relationship.

D1:WiFi Points & M5: Bike-sharing Point (0.73)

The strong positive correlation between the availability of WiFi access points and bicycle sharing stations across districts is likely due to both indicators reaching their respective target values (close to 100%) in most districts. This suggests that both WiFi access and bicycle sharing points are well-established across districts in the city. The correlation may not reflect a meaningful causal relationship but rather that the city of Barcelona is well-serviced in terms of both digital infrastructure and sustainable transport options.

D1: WiFi Points & W3: e-Waste Collection (0.71)

As with the previous correlation, the strong relationship between WiFi points and e-waste collection points can be explained by the high availability of both services in most districts. This correlation suggests that districts with good digital infrastructure also have better access to recycling facilities, although the relationship may be coincidental rather than causal. It likely reflects broader municipal efforts to ensure equitable access to both services across districts.

M5: Bike-sharing Points & W3: e-Waste Collection (0.98)

The near-perfect correlation between bicycle sharing points and e-waste collection facilities suggests that districts with strong cycling infrastructure are also well-equipped with recycling services. This correlation, again, likely reflects a coordinated urban policy to promote sustainability across multiple dimensions—encouraging cycling to reduce emissions and providing better facilities for recycling electronic waste.

7 Discussion

This chapter discusses the key findings and limitations of this research, providing interpretations per KPI.

7.1. Key Findings, Interpretations and KPI Limitations

D1: WiFi Points

Concerning the first KPI and simultaneously the same area, no notable variations appeared. A key result would be that all districts performed well, with all of them attaining a score over 0.8 and all but 3 districts even attaining a perfect score. It can thus be said that the WiFi coverage of Barcelona is excellent.

Limitations:
The dataset for WiFi points, sourced from the municipality, is recent, regularly updated, and verified. Consequently, the data quality is high, and no significant limitations were identified for this KPI.

ECR1: Energy Self-sufficiency

Regarding ECR1, the key point that stands out is the difference between district scores. With some districts attaining a score of 1 while other districts attain scores below 0.1 or even 0, these values stand out. This can be accounted for by the method of normalization that is used for this KPI. Since all values are compared relatively to one another, the values are not completely representative for the solar power produced - which is added on by the small percentage that municipal solar power production takes on compared to total energy consumption. Using already available municipal solar-power-potential maps A. de Barcelona (n.d.-b) , increasing municipal-generated solar energy can be accelerated.

Limitations:

- **Outlier Sensitivity**: Although unlikely residential outliers were removed, the dataset assumes that industrial and service sector outliers are valid. If these outliers do not accurately represent typical energy use, they could distort district-level energy consumption estimates.
- **Postal Code-District Overlap**: Energy consumption was distributed based on the spatial overlap of postal codes and district boundaries. For postal codes that do not align neatly with district boundaries, this method introduces potential inaccuracies. Adjustments for minor overlaps below a 5% threshold reduce errors but may still affect the energy consumption distribution.
- **Completeness of Energy Generation Data**: Missing coordinates for certain municipal buildings were manually added, which introduces a small margin of error. Additionally, outliers in solar energy production data may not represent typical energy generation, potentially skewing the self-sufficiency ratio.
- **Temporal Misalignment**: Energy consumption data reflects 2023, while solar energy generation data spans June 2023 to June 2024. This temporal discrepancy may affect the accuracy of the self-sufficiency ratio, as both energy production and consumption can fluctuate annually.

ECR2: Air Quality

For ECR2, all districts seem to have relatively comparable annual concentration of $PM_{2.5}$, PM_{10} and NO_2 (all being between 69-80 µg/m^3). The implication being that none of the districts achieve the

SDG target, means a city-wide approach would be needed to tackle air quality in Barcelona.

Limitations:

- **Temporal Limitation**: The dataset dates back to 2022. Using older data could impact accuracy, as more recent pollution data might reflect changes in air quality that are not captured here.
- **Range-Based Pollution Levels**: The dataset provides pollution levels in ranges (e.g., 20-30 g/m^3). For this analysis, the upper bound of each range was chosen to represent a worst-case scenario. This choice could result in slightly higher ECR2 scores, as selecting the lower bound might have led to different outcomes.
- **Potential Skew Towards Worst-Case Scenarios**: By focusing on the upper bound of pollution ranges, the results may portray a more severe air quality impact than actually exists. This approach was chosen to ensure caution but may somewhat skew the overall CCI score.

In summary, while these limitations introduce some degree of uncertainty, the worst-case approach offers a conservative perspective on air quality impacts within the CCI framework.

ECR3: Water Efficiency

The results of ECR3 show significant differences in absolute water use across districts. **Sant Martí**, a densely populated and expensive new development, and **Nou Barris**, a lower-income area with relatively high population but low water consumption, have the lowest water use per capita. In contrast, **Les Corts**, which has many hospitals and sports fields but a relatively small resident population, and **Ciutat Vella**, where tourism is high despite fewer residents, exhibit the highest water use. Further research might explore the correlation between the specific demographic and functional profiles of each district.

Limitations:

- **Data Conversion from Water Sectors to Districts**: Water usage data was available at the water sector level rather than by district. To estimate district-level water usage, each water sector's consumption was multiplied by the percentage of its area that overlaps with each district. This method assumes a uniform distribution of water usage across each sector, which may not hold true in practice.
- **Alignment with SDG Thresholds**: Although this approach introduces some assumptions, the focus on urban water usage aligns with the Sustainable Development Goal (SDG) thresholds, providing a partial benchmark for assessing water efficiency.

ECR4: EPC labels

The results for ECR4 indicate substantial progress is needed to meet the 2030 SDG target, with current scores ranging between 0.20 and 0.38, falling significantly short of the goal. A score of 1 represents a level 20% above category C, so the target is relatively modest, yet remains unmet. This underscores the importance of citywide policy initiatives for ECR4 rather than district-specific measures to achieve the necessary EPC label improvements across the city.

Limitations:

- **Frequent Data Updates**: EPC label data is updated on a weekly or biweekly basis, which helps minimize the risk of outdated or inconsistently applied labels, ensuring data remains relevant.
- **Handling of Duplicate Entries**: It is assumed that duplicate entries correspond to multiple apartments at the same address. However, if duplicates are not accurately filtered to represent unique households, this could skew the energy label distribution.

M1: Pedestrian Area

Eixample scores relatively low in pedestrian area per inhabitant, likely due to its high population density. As the most densely populated area in Barcelona, this results in limited public space per resident ("Facts and Figures about Barcelona", n.d.). **Sant Andreu** has an average number of inhabitants and a high percentage of industrial areas, resulting in fewer square meters of pedestrian space per inhabitant, as industrial areas typically offer less accessible public space.

Limitations:

- **Width Assumption**: Data points containing Linestrings without an area attribute were assigned a width of 2 meters. This is an estimated average width based on typical values of pedestrian areas in Spain. This estimated width may not represent actual conditions in all cases, and deviations could affect spatial accuracy in mobility assessments.

M2: Charging Stations

The distribution of charging points varies greatly between districts. Low-scoring districts are: **Horta-Guinardó, Nou Barris, Sant Martí**, and **Sants-Montjuïc**, where households are spread further apart. The greater distances between households increase the demand for charging points. The higher-scoring districts: **Eixample** and **Ciutat Vella**, where households are more densely packed, resulting in more households covered by each charging point.

Limitations:

- **Discrepancy Among Datasets**: Various datasets exhibited inconsistencies, making it difficult to identify the most accurate one. To address this, the dataset with the highest overlap was chosen (see chapter 4). However, this choice may still have limitations, as no dataset fully represents real-world conditions.
- **EV Charging Stations in M2**: Accessibility to EV charging stations is evaluated based on proximity only, without factoring in the number of available charging points. This simplification may lead to overestimating accessibility, especially in areas with high demand.

M3: Cycleway Length

Higher-scoring districts are **Sant Martí** and **Eixample**, these districts meet the threshold, possibly due to higher population density and increased demand for bike lanes from tourism. **Horta-Guinardó** (0.22), **Nou Barris** (0.29), **Sants-Montjuïc** (0.29), and **Sarrià-Sant Gervasi** (0.17) score low. These are suburban areas where demand for bike infrastructure appears lower due to less tourism and height differences within the districts Ajuntament de Barcelona (2011).

Limitations:

- **Data Granularity and Geometry Representation**: Bike lanes are represented as linestrings, which may not fully capture the physical width or real-world usage of the cycleways. If certain lanes are wider or narrower, this method does not reflect those variations, potentially leading to an oversimplified measure of bike infrastructure. Representing them solely as lines also ignores potential two-way or shared lanes, which could impact the perceived density and accessibility.

M4: Transit Stops

Barcelona performs excellently in public transport access, with all districts meeting the threshold for the number of public transport stops within walking distance, indicating that public transport is well accessible throughout the city.

Limitations:

- **Inconsistencies with Official Data**: According to Transports Metropolitans de Barcelona (2015), there are officially 2,623 bus stops and 165 subway stations, while Trenscat (2021) lists 56 tram stops. Our dataset, however, identifies 2,501 bus stops, 131 subway stations, and a discrepancy in tram stops (56 identified vs. 60 reported). These differences highlight possible data gaps and call for caution in interpreting results.

M5: Bike-sharing Points

Sarrià-Sant Gervasi: This is the only district that does not meet the bike-sharing threshold. Its hillside location and more spread-out households make access difficult and demand lower Ajuntament de Barcelona (2011).

Limitations:

- **Bike-Sharing Stations in M5**: Similarly, bike-sharing stations are assessed by location alone, disregarding the station's capacity to meet demand. This may lead to an oversimplified view of accessibility, as popular stations could experience shortages despite convenient placement.

W1: Waste Production

Ciutat Vella: This district has a normalized KPI score of 0.53, which could be explained by the relatively low number of residents in the old city center and its focus on recreation (Management, n.d.) & (Management, n.d.). The low score of **Eixample** can also be attributed to this, as it includes high-traffic areas like Sagrada Familia and Plaça de Catalunya, resulting in waste divided among fewer inhabitants.

Limitations:

- **Data Recency**: The dataset for waste production is from a 2019 study by Zheng (2019). Given that this data is five years old, it may not accurately reflect current waste generation patterns, which could have changed due to environmental policies, population growth, or shifts in public behavior. As a result, the findings may not capture recent trends in waste production.

W2: Waste Recycling

A clear density of waste bins is found in the districts of **Sant Montjuïc** and **Ciutat Vella**, resulting in relatively high scores for these districts and their adjacent areas. Conversely, **Nou Barris** and **Sant Andreu** score lower, as they are geographically further from these districts.

Limitations:

- **Shift in KPI Focus**: Originally, the CCI research used the percentage of solid waste recycled as a KPI. Since this data was unavailable, the measure was adapted to the percentage of households located within a 5-minute walking distance of a recycling bin. While this metric provides insights into recycling accessibility, it does not capture actual recycling rates or effectiveness, potentially affecting the interpretation of waste management performance.

W3: e-Waste Collection

Sarrià-Sant Gervasi: This is the only district that does not meet the threshold for e-waste collection points. Although this is not a major issue, increasing the number of e-waste collection points could enhance waste management and recycling in this area.

Limitations:

- **Data Source and Scope**: The dataset for e-waste collection points was obtained from the municipal website. It is important to note that the data does not differentiate between mobile, neighborhood, and area green points. This lack of distinction may be significant, as area green points tend to be more accessible and useful for non-residents compared to other types of collection points.
- **Walking Distance Consideration**: Since there is no specific Sustainable Development Goal (SDG) associated with this KPI, a walking distance of 10 minutes was established for accessibility measurement. However, had a shorter walking distance of 5 minutes been chosen, this could have substantially impacted the results by altering the perceived accessibility of e-waste collection points.

7.2. General Limitations

This section discusses general limitations that impact the data analysis across different KPIs, along with the variability, sensitivity, and uncertainty inherent in the research.

7.2.1. General Limitations on the Data Analysis

- **Reliance on OpenStreetMap (OSM) Data**: Several KPIs depend on OpenStreetMap (OSM) data, which can vary in quality and completeness due to its volunteer-based contributions. This may result in inconsistencies, especially in less populated areas, and variations in feature labeling due to a lack of standardized tagging. Additionally, certain infrastructure types, like pedestrian areas and transit stops, may be underrepresented, adding complexity to data retrieval through manual tag specification.
- **Coordinate Reference System (CRS) and Spatial Data Projection**: For spatial consistency, data was re-projected to a single coordinate reference system (EPSG:25831). While this re-projection improves overall spatial accuracy, it can introduce minor distortions. Such distortions may particularly impact smaller districts or areas where postal code boundaries are fragmented, potentially influencing district-level analyses.
- **Boundary Precision and Household Classification**: The use of OSMnx to define city boundaries is subject to inaccuracies in boundary polygon precision, potentially misclassifying households near city limits. Additionally, estimating household distribution across grid cells that intersect multiple district boundaries may not accurately reflect actual locations, especially in irregular or densely populated areas.
- **Exclusion of Grid Cells Beyond City Boundaries**: Some grid cells extending beyond Barcelona's boundaries are excluded from the analysis. This exclusion may result in minor undercounts of households in districts located near the city's edge.
- **Assumption of Uniform Household Distribution**: The analysis assumes an even distribution of households within each 100x100 meter grid cell. This assumption may not hold true, especially in mixed-use zones or clustered residential areas, where household concentrations can vary significantly.
- **Reliance on Outdated Household Data**: The household data utilized in this analysis relies on older sources that may not accurately represent current populations, particularly in rapidly changing neighborhoods. This reliance on outdated information could affect the accuracy of accessibility metrics.
- **Limitations in Spatial Joins and Geometric Operations**: Spatial joins and geometric operations are complex processes that can introduce small errors, especially in high-resolution data. Misalignments or slight inaccuracies in boundary data could affect the precise assignment of KPIs to districts, potentially skewing results for districts with irregular boundaries or those that share extensive borders with other districts.

These general limitations reflect the challenges of relying on open-source and spatial data in district-level analyses and highlight the care needed in interpreting results, particularly where boundaries and data completeness vary.

7.2.2. Variability and Uncertainty of Data

One of the key limitations of this project is the inherent variability and uncertainty associated with the data used. The datasets analyzed were primarily collected from a specific year, which may not fully represent long-term trends or seasonal variations. It is important to recognize that data can fluctuate significantly from year to year due to various factors, such as changes in environmental conditions, urban development, and population dynamics.

Moreover, the potential presence of anomalies in the data could further complicate interpretations. These anomalies may arise from outlier events, such as extreme weather occurrences or unexpected shifts in energy consumption patterns. The anomalies were addressed in the data analysis. However, there is still a chance that such irregularities could skew the results and impact the reliability of the conclusions drawn from the analysis.

To enhance the robustness of future studies, it is recommended to incorporate multi-year datasets that account for temporal variability. This approach would provide a more comprehensive understanding of the trends and patterns relevant to the research objectives, ultimately leading to more accurate and actionable insights.

7.2.3. Sensitivity

The results of the sensitivity analysis indicate that the chosen weightings significantly influence the scoring of the CCI, particularly for districts with high standard deviations. However, it is noteworthy that the highest and lowest ranks (1 and 10) remain consistent regardless of weighting adjustments. This consistency suggests that, despite the variability in mid-range scores, the analysis can reliably identify the best and worst-performing districts for the municipality on the CCI.

Weight selection, being inherently subjective, can be adjusted according to future priorities. For instance, if waste management is deemed more critical in subsequent analyses, weights can be recalibrated to reflect that emphasis. This adaptability ensures that the scoring remains relevant and aligned with specific goals or priorities of the municipality.

8
Conclusion and Recommendations

In this research, the main research question, focusing on evaluating and benchmarking district-level sustainability through a set of KPIs within Barcelona, was answered by assessing areas regarding Digitalization, Energy, Climate and Resources, Mobility, and Waste. The CCI reveals the overall effectiveness and limitations of district-level circularity measures in Barcelona, offering insights into areas where districts perform well and where improvement is needed.
The analysis demonstrated that Barcelona's WiFi coverage is excellent city-wide, with minimal discrepancies among districts. However, energy self-sufficiency varied significantly, highlighting a substantial gap in solar energy generation relative to consumption. Air quality metrics uniformly exceeded recommended thresholds city-wide, suggesting that localized efforts will likely have limited impact. Similarly, results in water efficiency were mixed, with marked differences based on district demographics. EPC scores were generally low, emphasizing the need for policy-level measures to meet the SDGs by 2030. Mobility assessments reflected a range of accessibility and infrastructure availability: transit stops and bike-sharing points were well-distributed, while pedestrian spaces and cycleways varied by district, revealing a strong link between infrastructure availability and population density. Waste production showed that tourist-heavy and high-density areas produced more waste per capita, while recycling infrastructure coverage was inconsistent, highlighting potential areas for improvement in waste management systems. E-waste recycling had a 100% coverage all over the city, except for Sarrià-Sant Gervasi.

The findings underscore the following key recommendations for the municipality of Barcelona:

- **Citywide Solar Energy Initiatives**: Given the disparity in district energy self-sufficiency, expanding citywide solar energy projects could promote a more balanced and sustainable energy production model across districts.
- **Comprehensive Air Quality Plan**: Air quality concerns require an overarching, citywide strategy to address emissions holistically, beyond district-specific initiatives.
- **Water Efficiency Education and Resources**: For districts with higher water usage, targeted educational campaigns and incentives to reduce consumption would complement the current focus on water sustainability. This would especially apply to Sants-Montjuïc, Sarrià-Sant Gervasi, Les Corts and Ciutat Vella.
- **Enhancing EPC Compliance**: City-wide policy should be designed to support all districts in meeting the EPC label requirements, given the city's current underperformance relative to the 2030 targets. This can be achieved by for instance increasing insulation throughout homes.
- **Infrastructure Investment**: Increasing the number of charging stations across most districts would enhance equitable access to sustainable transportation options. Additionally, expanding pedestrian areas, particularly in Eixample, and providing more bike-sharing points in Sarrià-Sant Gervasi would promote greater mobility and accessibility throughout the city.
- **Expanded Waste Management Programs**: For solid waste production, efforts should prioritize Ciutat Vella, which generates significantly more waste than other districts. Nou Barris can improve by ensuring that all households have a recycling bin within a 5-minute walk.

In summary, while Barcelona demonstrates significant progress in certain circularity areas, achieving balanced district-level performance necessitates strategic citywide efforts in energy, air quality, and waste management. These actions will support Barcelona's broader sustainability goals and contribute to achieving the SDG targets for a more sustainable urban future.

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A

Analysis of Absolute Results KPIs

A.1. Digitalization

Table A.1: Results of Digitalization

District	**D1** [% households in range]
Ciutat Vella	100
Eixample	100
Gràcia	98.7
Horta-Guinardó	98.8
Les Corts	84.3
Nou Barris	93.7
Sant Andreu	100
Sant Martí	100
Sants-Montjuïc	98.8
Sarrià-Sant Gervasi	81.6

D1: WiFi Points

The D1 column in Table A.1 represents the percentage of households within each district that are within a 10-minute walking distance of a public WiFi point.

Ciutat Vella, Eixample, Sant Andreu, and Sant Martí stand out with full coverage, reaching 100% of households within a 10-minute walking distance of a public WiFi point. At the other end of the spectrum, Sarrià-Sant Gervasi has the lowest coverage, with only 81.6% of households within range of a WiFi point. This relatively low percentage suggests significant room for improvement in public internet access, making Sarrià-Sant Gervasi a priority area for expanding digital infrastructure to match the high levels seen elsewhere in the city. Les Corts also shows a lower level of WiFi accessibility, with 84.3% of households within a 10-minute walk.

Energy, Climate and Resources

Table A.2: Results of ECR (Part 1: ECR1, ECR2, and ECR3)

District	**ECR1** [generated/consumed [%]]	**ECR2** [$\mu m/m^3$]			**ECR3** [l/inhab/day]
		NO_2	**PM_{10}**	**$PM_{2.5}$**	
Ciutat Vella	0.11	41.1	28.4	15.6	203
Eixample	0.10	46.2	29.3	19.5	151
Gràcia	0.06	35.7	27.0	15.9	124
Horta-Guinardó	0.27	31.4	28.4	15.8	124
Les Corts	0.08	33.0	26.8	16.0	216
Nou Barris	0.16	31.2	26.6	15.8	98.2
Sant Andreu	0.16	32.6	27.1	16.3	116
Sant Martí	0.27	32.8	28.4	18.7	90.7
Sants-Montjuïc	0.04	32.7	28.7	15.5	191
Sarrià-Sant Gervasi	0.05	31.3	25.8	15.8	195

Table A.3: Results of ECR (Part 2: ECR4)

District	**ECR4** [label A-G]						
	A	**B**	**C**	**D**	**E**	**F**	**G**
Ciutat Vella	71	274	1133	2354	12 877	3031	6076
Eixample	193	896	3567	6925	34 697	6698	8925
Gràcia	110	249	1210	2460	14 637	3390	5122
Horta-Guinardó	63	224	1013	2087	14 637	4013	6673
Les Corts	42	197	779	1759	8486	1545	2025
Nou Barris	38	141	868	1610	13 239	3855	5954
Sant Andreu	70	230	927	1870	12 122	2742	4190
Sant Martí	173	418	1711	3748	21 198	4290	6011
Sants-Montjuïc	80	257	1209	2692	18 343	3970	6377
Sarrià-Sant Gervasi	147	402	1778	4162	18 027	3493	4734

ECR1: Energy Self-sufficiency

Horta-Guinardó and Sant Martí have the highest energy self-sufficiency, with values of 0.27%. Sants-Montjuïc has the lowest value at 0.04%, followed by Sarrià-Sant Gervasi at 0.05%, suggesting these districts are highly dependent on external energy sources. Most other districts range between 0.10 and 0.16, with limited self-sufficiency overall.

ECR2: Air Quality

Eixample shows the highest pollution levels across all three metrics: NO_2 at 46.2 µg/m^3, PM_{10} at 29.3 µg/m^3, and $PM_{2.5}$ at 19.5 µg/m^3, indicating significant air quality concerns. Nou Barris and Sarrià-Sant Gervasi have relatively lower values, with NO_2 around 31 µg/m^3, PM_{10} around 26.6–27 µg/m^3, and $PM_{2.5}$ close to 15.8 µg/m^3. Overall, Eixample stands out as a high outlier in air pollution, while Nou Barris and Sarrià-Sant Gervasi are low outliers, indicating better air quality in these areas.

ECR3: Water Efficiency

Nou Barris and Sant Martí show the lowest water usage, with values of 98.2 l/inhab/day and 90.7 l/inhab/day, respectively. These districts seem to be more efficient in water consumption. Les Corts and Ciutat Vella have the highest water usage, with 216 and 203 l/inhab/day, respectively, suggesting higher water consumption per capita. Most other districts fall between 116 and 195 l/inhab/day, with Nou Barris and Sant Martí as low outliers, indicating better water efficiency.

ECR4: EPC Labels

Across the districts, a clear trend emerges, with the E label dominating most building stocks. This prevalence of lower-efficiency buildings, particularly in labels E, G, and D, highlights a widespread need for energy efficiency improvements in several areas. Eixample and Sant Martí both exhibit a large share of E-labeled buildings, with 34,697 and 21,198 buildings, respectively. Following E, G and D labels are also common, indicating that a substantial portion of each district's buildings fall into the lower efficiency range. This pattern suggests that both districts would benefit from targeted energy efficiency interventions. In Sarrià-Sant Gervasi and Les Corts, E is again the most frequent label, with 18,027 and 8,486 buildings, respectively. While Sarrià-Sant Gervasi has a relatively higher proportion of high-efficiency labels (A and B), these are still outnumbered by buildings in the E and G categories, pointing to an overall lower-efficiency trend across the district.

Nou Barris, Ciutat Vella, and Horta-Guinardó all display a similar structure, with E as the dominant label. Nou Barris has 13,239 E-labeled buildings, while Ciutat Vella and Horta-Guinardó follow with 12,877 and 14,637 buildings, respectively. G and F labels are also well-represented in these districts, reinforcing the need for improvement. Gràcia and Sants-Montjuïc present a similar distribution, with E labels (14,637 and 18,343, respectively) leading the count, followed by G and F. This pattern underscores the concentration of lower-efficiency buildings and the limited presence of high-efficiency labels (A and B) across both districts.

Overall, there is a dominance of E, G, and F labels across districts. While a few districts, such as Sarrià-Sant Gervasi, show a modest presence of higher-efficiency buildings, the general landscape points to bad EPC-labels, particularly in districts with high proportions of E-labeled buildings.

Notable Cases

Distinct patterns across the Energy, Climate, and Resources categories (ECR1, ECR2, ECR3, ECR4) highlight several trends among the districts:

- Eixample shows high air pollution levels (ECR2) and a large share of buildings in lower-efficiency labels E, G, and D.
- Sant Martí and Nou Barris demonstrate efficient water usage (ECR3) and moderate energy self-sufficiency (ECR1), yet both districts have a high prevalence of E and G labels in Sant Martí, and E, F, and G labels in Nou Barris.
- Sarrià-Sant Gervasi exhibits relatively good air quality (ECR2) and includes some high-efficiency buildings, though E and G labels remain predominant across the district.
- Les Corts and Nou Barris contain high numbers of E and G labeled buildings, indicating a notable presence of lower-efficiency buildings in both districts.

Mobility

Table A.4: Results of Mobility

District	**M1** [m^2 per 100 inhab]	**M2** [% households in range]	**M3** [km/km^2]	**M4** [% households in range]	**M5** [% households in range]
Ciutat Vella	1040	61	2.8	100	100
Eixample	361	62	9.2	100	100
Gràcia	611	52	1.7	99.7	93.7
Horta-Guinardó	871	31	0.9	99.8	92.2
Les Corts	1121	55	2.7	99.5	97.4
Nou Barris	703	29	1.2	99.2	86.6
Sant Andreu	578	58	2.4	100	100
Sant Martí	1045	33	5.4	100	100
Sants-Montjuïc	1213	34	0.9	99.9	99.7
Sarrià-Sant Gervasi	815	47	0.7	95.9	74.4

M1: Pedestrian Area

The M1 column in Table A.4 represents the total pedestrian area (in m² oer 100 inhabitants) per district. At the top end, Sants-Montjuïc, Les Corts, and Sant Martí offer the most pedestrian space

per resident. These districts, with their generous square meters per capita, suggest a landscape that is either less densely populated or intentionally designed with expansive public areas. Residents here likely experience a more open, less crowded urban environment, ideal for leisure and mobility.
Conversely, Eixample stands out at the lower extreme, offering the least pedestrian space per resident. This district is likely the most urbanized and densely populated, with limited public space relative to its population. The scarcity of pedestrian area suggests a compact environment where footpaths may feel crowded, and open space is at a premium.

M2: Charging Stations

The M2 values in Table A.4 represent the percentage of households within each district that are within a 5-minute walking distance of a charging point. At one extreme, Eixample and Ciutat Vella have the highest percentages, with over 60% of households within a short walk to a charging point. This suggests a dense and well-distributed network of charging stations, catering effectively to residents' needs in these districts.
On the opposite end, districts like Nou Barris, Horta-Guinardó, Sant Martí and Sants-Montjuïc have the lowest accessibility, with only around a third or less of households within walking distance of a charging point. For residents, this means that access to charging stations is likely more limited, which may impact convenience, especially for those relying on electric vehicles. This lack of accessibility could suggest either a less urbanized setup, where infrastructure is more dispersed, or simply a lower prioritization of charging points in these areas.

M3: Cycleway Lengths

The M3 column in Table A.4 represents the total length of cycleways (in km per km^2) within each district, indicating the extent to which cycling infrastructure is developed relative to the area size of each district. This metric highlights how accessible and prioritized cycling is across different areas in Barcelona.
At one extreme, Eixample has the highest cycleway density at 9.2 km/km^2. This suggests that Eixample is relative highly conducive to cycling, with a well-developed and dense network of cycle paths. In contrast, Sarrià-Sant Gervasi, Sants-Montjuïc and Horta-Guinardó have the lowest values for M3, with only 0.7 and 0.9 km/km^2 of cycleways, respectively. This low density indicates that cycling infrastructure is limited, potentially making cycling less practical or safe for residents in these areas. These districts might be more car-oriented or have a less developed cycling culture, or they may feature topographies that make cycling infrastructure less feasible to implement widely.

M4: Transit Stops

The results of M4 in Table A.4 show that nearly all districts in Barcelona already have sufficient access to public transportation within a 5-minute walking distance. In districts such as Ciutat Vella, Eixample, Sant Andreu, and Sant Martí, 100% of households are within easy reach of a public transit stop, ensuring that every resident can access public transport within minutes. This near-universal coverage highlights a well-established and accessible transit network across the city, meeting the mobility needs of the vast majority of residents.
A few other districts, like Horta-Guinardó (99.8%) and Nou Barris (98.2%), fall just shy of 100% but still offer nearly complete coverage. Public transportation here is likewise highly accessible, with only a small portion of households slightly beyond the 5-minute range. These minor gaps could be bridged with minimal adjustments, allowing these districts to easily reach full coverage.
Sarrià-Sant Gervasi has the lowest coverage at 95.9%. Although this percentage is a bit lower than in other districts, it remains high, indicating that the vast majority of residents in this area already have convenient access to public transport. While Sarrià-Sant Gervasi may benefit from some additional transit stops to reach full coverage, its existing level is still quite strong and adequate for most residents.

M5: Bike-sharing Points

The M5 column in Table A.4 represents the percentage of households within each district that are within a 10-minute walking distance of a shared bicycle point. This metric reflects how accessible bicycle-sharing options are to residents across Barcelona, providing insights into the coverage and convenience of shared mobility options in the city.
Most districts demonstrate strong coverage, with Ciutat Vella, Eixample, Sant Martí, Sant Andreu, and Sant Martí reaching 100% of households within a 10-minute walk of a shared bicycle point. This

indicates excellent access to bicycle-sharing services in these areas. Residents in these districts have optimal access to shared bicycles, promoting easy adoption of cycling for short trips and enhancing sustainable mobility.
At the lower end, Sarrià-Sant Gervasi has the lowest M5 value, with 74.4% of households within range of a shared bicycle point. Although this percentage is significantly lower than other districts, it still represents reasonable access, covering nearly three-quarters of households. However, it suggests that shared bicycle infrastructure in Sarrià-Sant Gervasi is less developed or more dispersed.

Notable Cases

Across the five mobility categories (M1, M2, M3, M4, M5), distinct patterns emerge among the districts:

- Sant Martí shows high accessibility across nearly all mobility metrics, with full coverage in public transit (M4 at 100%) and shared bicycle points (M5 at 100%), as well as a high pedestrian area per capita (M1 at 1045 m^2/100 inhabitants). It also has a relatively high cycleway density (M3 at 5.4 km/km^2), highlighting a commitment to diverse, accessible mobility options. However, the accessibility to charging points (M2 at 33%) is relatively low compared to other metrics, suggesting room for improvement in electric vehicle infrastructure to better support a more comprehensive mobility network in the district.
- Sarrià-Sant Gervasi ranks relatively low across most mobility metrics, indicating a need for improvement in several areas. It has the lowest accessibility to shared bicycle points (M5 at 74.4%) and the lowest cycleway density (M3 at 0.7 km/km^2), making cycling and shared mobility options less convenient for residents. Additionally, it has the lowest coverage for public transit (M4 at 95.9%), which, while still fairly high, falls short compared to other districts. Overall, Sarrià-Sant Gervasi appears to be less well-equipped in terms of mobility infrastructure, with room for enhancement across various categories.
- Sants-Montjuïc shows strong performance in pedestrian area per capita (M1 at 1213 m^2/100 inhabitants) and full coverage in public transit (M4 at 99.9%) and shared bicycle points (M5 at 99.7%). However, it has one of the lowest cycleway densities (M3 at 0.9 km/km^2), indicating that while residents have abundant pedestrian space and good access to transit and bike-sharing options, cycling-specific infrastructure is relatively sparse.
- Nou Barris presents an interesting case with high pedestrian space (M1 at 703 m^2/100 inhabitants) and near-full transit access (M4 at 98.2%), yet has the lowest accessibility to charging points (M2 at 29%) and moderate access to shared bicycle points (M5 at 86.6%). This could suggest a focus on pedestrian and transit infrastructure over electric vehicle and bicycle-sharing infrastructure, potentially indicating an area for future investment.

Waste

Table A.5: Results of Waste

District	**W1** [kg/inhab/day]	**W2** [% households in range]	**W3** [% households in range]
Ciutat Vella	2.25	100	99.7
Eixample	1.75	82.0	99.2
Gràcia	1.22	91.7	98.5
Horta-Guinardó	0.84	54.7	96.5
Les Corts	1.53	60.4	93.7
Nou Barris	0.78	29.8	96.7
Sant Andreu	1.02	44.2	99.9
Sant Martí	1.05	56.9	97.9
Sants-Montjuïc	1.03	70.3	97.5
Sarrià-Sant Gervasi	1.52	67.3	77.0

W1: Waste Production

Ciutat Vella has the highest value at 2.25 kg/inhab/day. This value suggests that Ciutat Vella has a higher level of waste production per inhabitant. Nou Barris has the lowest value at 0.78 kg/inhab/day, which is less than half of Ciutat Vella's production rate. This could indicate lower consumption or more effective waste management practices, but it stands out as an outlier on the low end. Most other districts are clustered between 0.84 (Horta-Guinardó) and 1.75 (Eixample), making Ciutat Vella a high outlier and Nou Barris a low outlier.

W2: Waste Recycling

Ciutat Vella has full coverage with 100% of households within a 5 minute walking range, followed by Gràcia at 91.70%. This suggests that these districts have high accessibility to recycling facilities. Nou Barris has the lowest coverage, with only 29.83% of households within range, making it a outlier. This low percentage could indicate infrastructure gaps or geographical challenges in providing access to recycling. Other districts vary between 44.24% (Sant Andreu) and 82.02% (Eixample), with Nou Barris standing out distinctly as the least covered district.

W3: e-Waste Collection

Ciutat Vella and Sant Andreu again show high accessibility, with 99.72% and 99.94% of households in a 10 minute walking range, respectively. Sarrià-Sant Gervasi has a notably lower percentage at 77.02%, marking it as an outlier on the low end. This could indicate less coverage or more dispersed waste facilities in this district. The rest of the districts fall within 93% to 98%, so Sarrià-Sant Gervasi is the only one that stands out in this metric.

Notable Cases

Across the three waste categories (W1, W2, W3), distinct patterns emerge among the districts:

- Ciutat Vella stands out as a consistent high performer in accessibility, with full coverage in both recycling (W2) and e-waste collection (W3), but it also has the highest waste production per capita (W1 at 2.25 kg/inhab/day).
- Nou Barris appears as a low outlier in both waste production (W1 at 0.78 kg/inhab/day) and recycling accessibility (W2 at 29.83%). The limited access to recycling facilities might impact waste behaviors or indicate infrastructure gaps in the district.
- Sarrià-Sant Gervasi shows low accessibility to e-waste collection (W3 at 77.02%) despite moderate waste production (W1 at 1.52 kg/inhab/day). This suggests a specific gap in e-waste infrastructure compared to other districts.